COMPARISON OF NEURAL NETWORK ARCHITECTURES FOR PREDICTION PROBLEM

by

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TH
EE/1999/M
R14c

DEPARTMENT OF ELECTRICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY KANPUR

January, 1999

COMPARISON OF NEURAL NETWORK ARCHITECTURES FOR PREDICTION PROBLEM

A Thesis submitted

in Partial Fulfilment of the Requirements

for the Degree of

Master of a Technology

by

GOPAL RAM

to the

DEPARTMENT OF ELECTRICAL ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY KANPUR

JANUARY 1999

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CERTIFICATE

This is to certify that the work contained in thesis entitled **"Comparison of Neural Network Architectures for Prediction Problem"** by Mr. Gopal Ram has been carried out under my supervision and that has not been submitted elsewhere for a degree.

Premkalra

Dr. Prem Kumar Kalra
Professor
Department of Electrical Engineering
Indian Institute of Technology, Kanpur

Dedicated to

My

Parents

Acknowledgement

It is a great pleasure to express my deepest gratitude to my guide and adviser Professor **Dr. P. K. Kalra** for his inspiring guidance and patient supervision throughout the programme. Besides the academic guidance, his words always provided me with a moral support at times when things appeared difficult to me. I am thankful to the tremendous facilities in the lab and the freedom of work given by him.

I wish to thank all my friends and well wishers who made my stay at I. I. T. Kanpur all these years a memorable and pleasant experience. The unstinting help rendered to me by my friends Vijay, Phani Kumar, Ritesh Pila, Jay, Karthik, Mashuq and Pratibha and I am indebted to Mr. P. Phani Kumar and Mr. K. Vijay without whose help it was inconceivable to finish the thesis in time. I thank Mr. Sandhitshu Ranjan Das (Sandy),and Mr. Sinha (Prabhuji) for their valuable suggestions.

I am very much thankful to the Almighty who provided me the inner strength to complete this work successfully.

I have no words to express my thanks to my parents and my maternal uncle Shree Kheemaram who have always been a constant source of inspiration to me.

GOPAL RAM

ABSTRACT

The neuron has two processing functions, i.e. aggregation and activation function. The aggregation of input to the neuron is performed through weighted sum. The aggregation of input is passed through activation function to generate the output of the neuron. The performance of the neural network depends upon the characteristics of the neuron. The total number of connecting weights among neurons, the optimization algorithms and their parameters constraint the learning time for the neural networks.

This thesis deals with study of conventional back propagation algorithm for learning of neural networks having neurons with different types of activation functions. The study reported here includes the prediction of short-term power demand, and interest rate forecasting. These two prediction problems have been solved using conventional neural network architecture and non-conventional architecture of the neural networks.

The results obtained for prediction of either power demand or interest rate demonstrate directly the quality of prediction as function of activation function. The conventional architecture produces relative better results compared to non-conventional architectures for power demand forecast, whereas recurrent neural network performs better for interest rate prediction compared with other reported architectures.

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Chapter 1

Introduction

The method for processing information as understood in human brain is through neurons. These neurons are interconnected massively in parallel [1-4]. A schematic of the same has been shown in Fig. 2.1. The mathematical model of a neuron is as follow:

$$y_i = f\left(\sum_{i=1}^{N} w_i x_i + w_0\right) = f\left(\sum_{i=0}^{N} w_i x_i\right) \qquad \text{where } x_0 = 1$$

where,

w_i = weight assigned to input

x_i = input to neuron

y_i = output of neuron

w_0 = threshold for neuron

There is no restriction on w_i. Weight can be static, probabilistic, dynamic, fuzzy, and stochastic. Weights are defining decision boundaries in Artificial Neural Network (ANN.). These decision boundaries may be time dependent or independent. The dimension of the decision boundaries is a direct function of number of inputs to the ANN. Non-linear models for controls; pattern recognition, optimization and regression require

non-linear terms to depict the relationship between input and output. This is achieved using a sigmoidal function as shown in Fig. 2.2. The sigmoidal function output (Y_i) is defined as

$$Y_i = \frac{G}{1+e^{-\beta(y_i)}}$$

G = gain of sigmoidal function and

β = abruptness/slope indicator

The output of sigmoidal function is 0.5 for y_i = 0, G = β = 1.0, and y_i increases for same values of G and β the Y_i became zero.

There are large numbers of learning methods for Artificial Neural Network [5]. Learning means determining (i) interconnection among various neurons and (ii) strength of interconnections. This process also known as memorization. At this point, a brief introduction of supervised and unsupervised learning would be helpful. Unsupervised learning, also known as self organisation, does not require an external teacher and relies only upon local information. This type of learning is used to generate classification of data presented to ANN. Learning algorithms uses "follow the leader" approach. Vigilance parameter and metric function control clustering.

Supervised learning needs an external teacher and knowing before hand the target values performs the error correction. The error is defined as follows:

$$E = \sum_{i=1}^{N}(O_i - T_i)^2$$

Where,

O_i = output of ANN

T_i = target value (desired output)

E_i = Error

Supervised learning is further classified as: (i)structural learning (output is independent of past values) and (ii) temporal learning (output depends upon past history).

The second type supervised learning is employed for Short-Term Load Forecasting (STLF) and Financial Forecasting.

Artificial Neural Networks (ANNs) have been widely applied to obtain solution to prediction problem [7]. The ANNs have also been tested for prediction problems such as power demand and interest rate [10]. Variants of ANNs used for predictions and control has been reviewed and reported in literature [8]. The literature survey showed that the major emphasis to develop the variants of ANN is on its learning algorithms. Further, it has also been proposed in recent papers [11-15] that learning algorithms for ANNs can be made efficient by incorporating new neuron models [6]. The development of neuron model not only reduces the complexity of architecture, learning time but also contributes in reducing hardware requirements.

The study reported in thesis has been carried out from viewpoint that can one achieve advantages of new neuron model by appropriately adjusting the thresholding functions of the neurons. To investigate the influence of thresholding functions on the quality of prediction the following problem has been defined.

1.1 Problem Definition

The standard feedforward neural network is generally developed using backpropagation algorithm (BPA) of either first order or second order. The neuron which forms the basic unit of ANN is realized by aggregation function and thresholding

function. The most commonly used aggregation function is weighted sum, which is passed through the thresholding function i.e. sigmoidal function (most commonly used).

In the literature survey, author has realized that influence of thresholding function on the performance of ANN has not been fully justified, further all thresholding functions have not been evaluated for a given problem. With the objective of evaluating the influence of thresholding function the following tasks have been set forth

(i) Study of influence of thresholding function for conventional ANN models for predicting STLF (Short Term Load Forecasting) and interest rates.

(ii) Study of influence of thresholding function for non-conventional ANN models for predicting STLF (Short Term Load Forecasting) and interest rates.

1.2 Organization of Thesis

A brief introduction of neuron model along with its limitations has been discussed in Chapter1.

In chapter 2, the standard backpropagation neural network has been studied to predict the power demand and interest rate with various thresholding functions.

In chapter 3, the non-conventional neural network has been tested to find the best modal for prediction of power demand and interest rate with various architecture and thresholding function.

Conclusions are given in chapter 4 and this chapter also includes the future scope in this field.

Chapter 2

Conventional Neural Network Models for Prediction

2.1. Introduction.

Artificial Neural Networks (ANN) have been used in literature for prediction of Short- Term Load Forecasting (STLF) [12], and financial forecasting [15]. Both problems have been solved using back propagation algorithm (BPA) and its variants. However basic neuron model used to solve above mentioned problems consists of weighted sum of all the inputs as aggregation function and sigmoidal function as the thresholding function. It is believed that aggregation function thresholding function play an important role for input and output mapping of data. The study reported in this chapter demonstrate influence of thresholding function upon the quality of prediction, using standard BPA for both problems stated above.

2.2. Artificial Neural Network Structure.

The basic building block of ANN is a neuron (depicted in Figure 2.2 as a circle). The neurons are connected by **weights**, (depicted as lines) which are applied to values passed from one neuron to the next. A group of neurons is called **a slab**. Neurons are also grouped into layers by their connection to the outside world, as shown in figure 2.1. For example, if a neuron receives data from outside of the network, it is considered to be in the input layer. If a neuron contains the network's predictions or classifications, it is in the output layer. Neurons in between the input and output layers are in the hidden layer(s). A layer may contain one or more slabs of neurons.

2.2.1. Link

A link is the connection or set of weights between the slabs or groups of neurons in a network. Each link can have an individual learning rate and momentum, and the weight can be fixed in a particular range as required.

2.2.2. Learning

The network "learns" by adjusting the interconnection weights between layers. The outputs the network is producing are repeatedly compared with the correct outputs and each time the connecting weights are adjusted slightly in the direction of the correct outputs. Eventually, if the problem can be learned, a stable set of weights adaptively evolves and will produce good outputs for all of the sample predictions. The secret to building successful neural networks is to know when to stop training. Too little training may not make the network learn the presented patterns while too

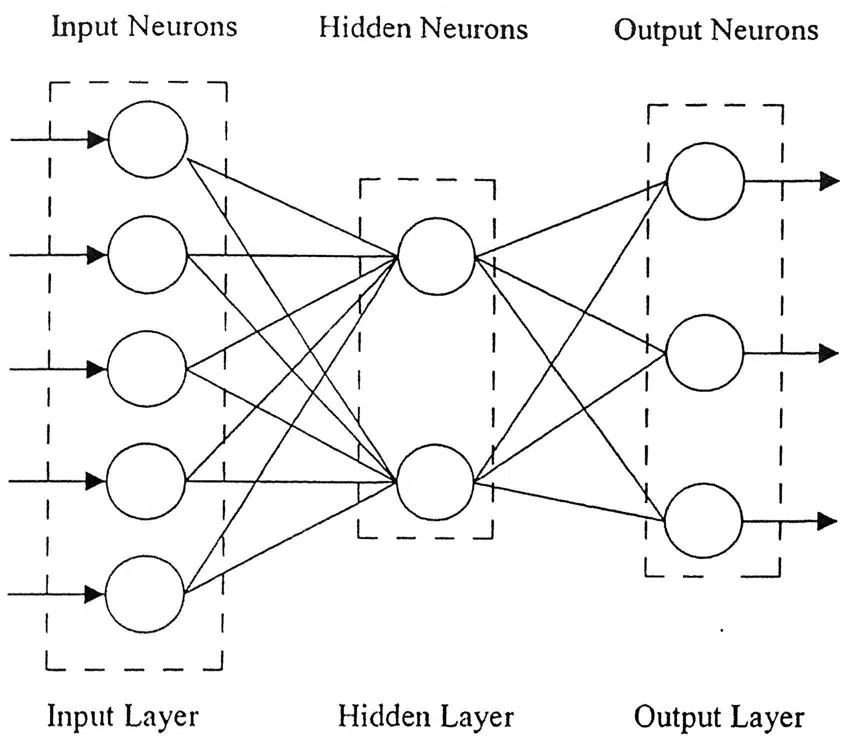


Figure 2.1: Neural Network Structure

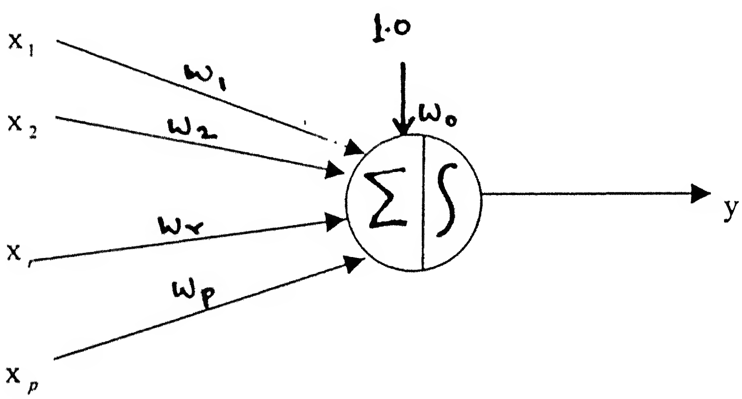


Figure 2.2: Model of a Neuron

much training can make it memorize the patterns and thereby losing the generalization character.In this work, two types of learning are studied for ANN. i.e.

(1). **Rotational** :-This select training patterns in the order they appear in the Pattern file., and

(2). **Random.** :- This option randomly chooses the training patterns.

2.3. Architecture of Artificial Neural Network.

An ANN has input, hidden and output layers. The number of neurons in input and output are constrained by the number of inputs and outputs whose relationship is to be established, whereas the number of hidden layers and the number of neurons in each layer are to be decided by mapping requirements of the inputs and outputs. This is performed by trial and error during training phase. Once the number of hidden layers and the number of neurons in each layer have been finalized, the model is tested on available data to avoid under or over training of the network.

A total of P sets of training patterns are assumed to be available. Inputs of these patterns are imposed on the input layer. The ANN is trained to the corresponding target vector i.e. the set of outputs. The training continues until a certain stop-criterion is satisfied. Typically, training is halted when the average error between the desired and actual outputs of the neural network over the P training data sets is less than a predetermined threshold. The training time required is dictated by various elements including the complexity of the problem, the number of data, the structure of network, activation function, hidden neurons, and the training parameters used.

2.3.1. Architecture of Standard Back-Propagation Networks.

Following architectures of ANN have been used for standard BPA. Neural network with each layer connected to the immediately preceding layer with one hidden layer.as depicted in Figure 2.3., similarly with two hidden layer and with three hidden layer.

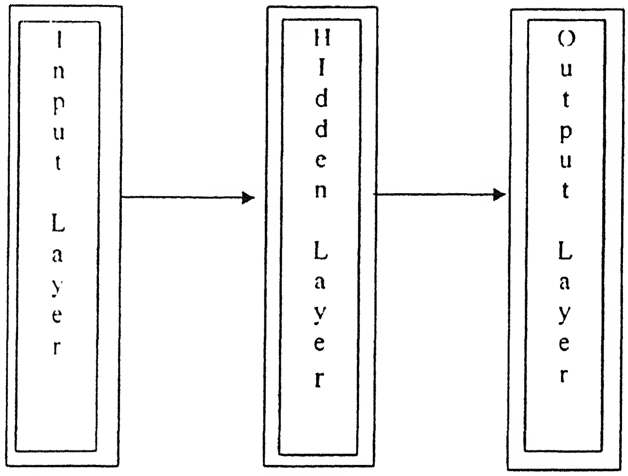


Figure 2.3: Block diagram of ANN with a Hidden Layer

2.4. Activation Function

The hidden layer produces outputs based upon the sum of weighted values passed to them. So does the output layer. The way they produce their outputs is by applying an "activation" function to the sum of the weighted values. The activation function, also called the threshholding function, maps this sum into the output value, which is then "fired" on to the next layer. Although the logistic function is the most popular, there are other functions which are also used.

2.4.1. Logistic (Sigmoid logistic)

This function is found to be useful for most of the cases. It maps values into the range (0,1) as shown in Figure 2.4.

logistic:

$$f(x) = \frac{1}{(1 + \exp(-x))}$$

symmetric_logistic:

$$f(x) = \frac{2}{(1 + \exp(-x))} - 1 \qquad \text{scale } [-1,1]$$

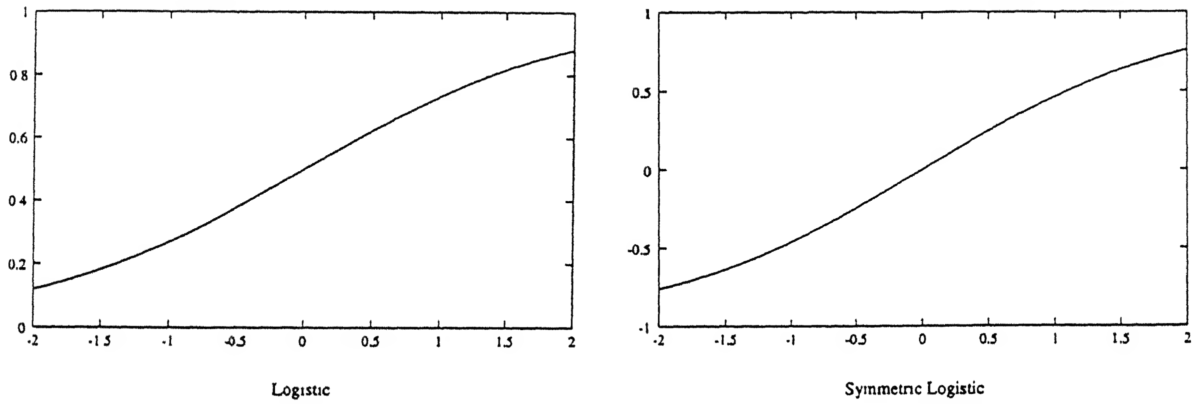


Figure 2.4: Logistic and Symmetric logistic activation function.

2.4.2. Linear

Use of this function is generally limited to the output slab. It is useful for problems where the output is a continuous variable. It sometimes prevents the network from producing outputs with more error near the min or max of the output scale. In Fig. 2.5 Linear function is depicted.

linear function

$$f(x) = x$$

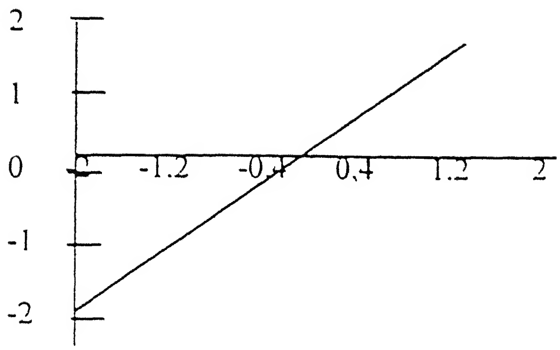


Fig 2.5: Linear activation function.

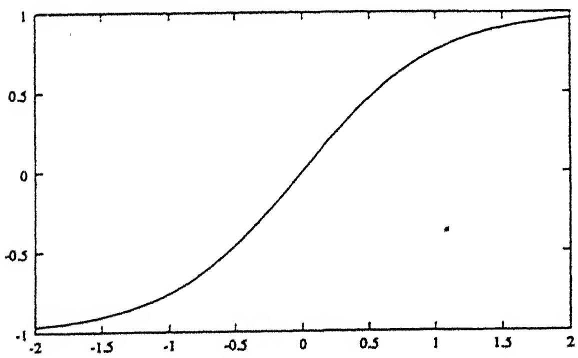
2.4.3. Tanh (hyperbolic tangent)

It is sometimes better for continuous valued outputs especially if the linear function is used on the output layer.

$$f(x) = \tanh(x)$$

Its another variation is defined as shown in figure 2.6.

$$f(x) = \tanh(1.5x)$$



tanh

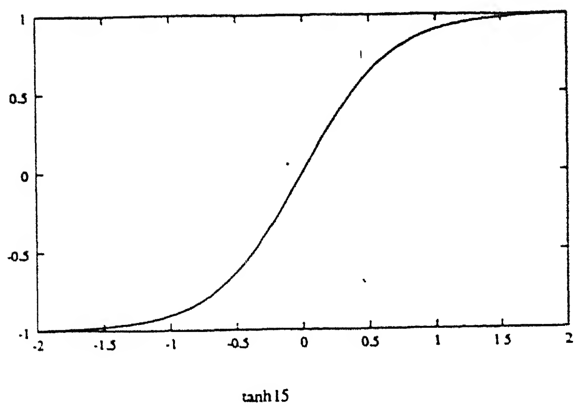


Fig. 2.6: Hyperbolic Tangent activation function

2.4.4. Sine

If it is used it in the first hidden layer then the inputs are scaled into the range [-1,1] and if used in the output layer, output is scaled into the range [-1,1] as shown in figure 2.7.

$$f(x) = \sin(x)$$

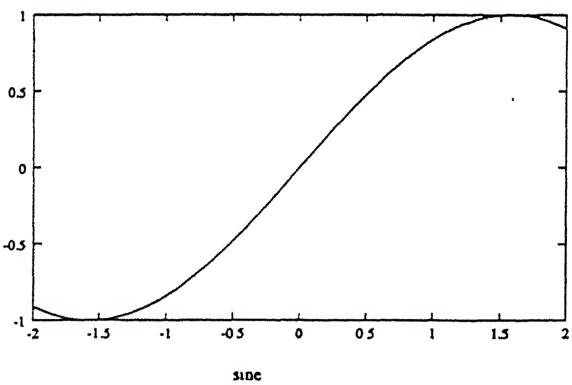


Fig.2.7: Sine activation function

2.4.5. Gaussian

This function is unique, because unlike the others, it is not an increasing function. It is the classic bell shaped curve, which maps high values into low ones,

and maps mid range values into high ones. It is used it in the hidden layer, and standard logistic function in the output layer. Output layer as shown in figure 2.8

Gaussian:

$$f(x) = \exp(-x^2)$$

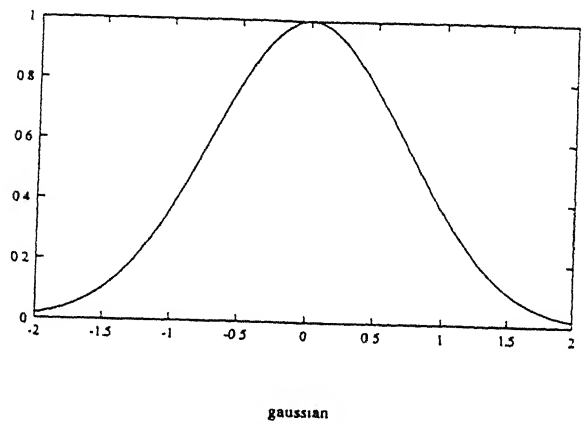


Fig.2.8: Gaussian activation function

Gaussian-complement:

$$f(x) = 1 - \exp(-x^2)$$

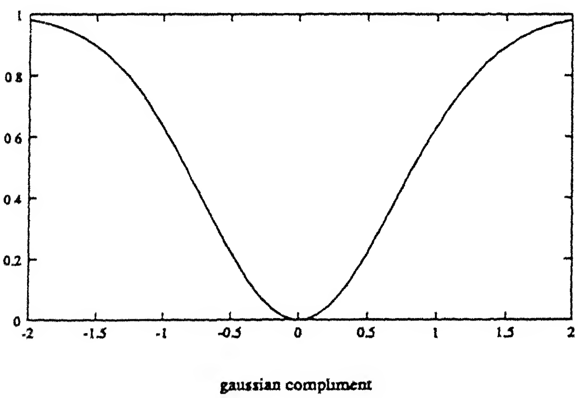


Fig 2.9: Gaussian compliment activation function

2.5. Weight Updation Schemes.

The BPA algorithm is based on steepest descent method for solving non-linear optimization problem. The details of the algorithm is reported in the literature [9]. Generally learning rate and momentum factor influence the convergence of the algorithms.

2.5.1. Learning Rate

Each time a pattern is presented to the network, the weights leading to an output node are modified slightly during learning, in the direction required to produce a smaller error the next time the same pattern is presented. The amount of weight modification is the learning rate times the error. For example, if the learning rate is 0.5, the weight change is one half the error. The larger the learning rate, the larger the weight changes, and the faster the learning will proceed. Oscillation or non-convergence can occur if the learning rate is too large.

2.5.2. Momentum Factor.

Large learning rates often lead to oscillation of weight changes and learning never completes, or the model converges to a solution that is not optimum. One way to allow faster learning without oscillation, is to make the weight change a function of the previous weight change to provide a smoothing effect. The momentum factor determines the proportion of the last weight change that is added into the new weight change.

2.6. Parameters Used for Selection of Best Result

2.6.1. R Squared: --

R squared, the coefficient of multiple determination, is a statistical indicator. A perfect fit would result in an R squared value of 1, a very good fit near 1, and a very poor fit near 0. If our neural model predictions are worse than we could predict by just using the mean of our sample case outputs the R squared value will be 0. The formula for R squared is the following.

$$R^2 = 1 - \frac{SSE}{SS_{yy}}$$

where,

$$SSE = \Sigma(y - \hat{y})^2,$$

$$SS_{yy} = \Sigma(y - \bar{y})^2,$$

y = the actual value,

$\hat{y}$ = the predicted value of y, and

$\bar{y}$ = the mean of the y values.

2.6.2. Correlation Coefficient (r): --

This is a statistical measure of the strength of the relationship between the actual vs predicted outputs. The 'r' coefficient can range from -1 to +1. The closer r is to 1, the stronger the positive linear relationship, and the closer r is to -1, the stronger the negative linear relationship. When r is near 0, there is no linear relationship.

2.7. Short Term Power Demand Prediction

A power system can be viewed as an interconnection of three main subsystems viz. generating unit, transmission and distribution network and loads. The modelling of generators and transmission and distribution networks for different types of studies has become almost standard. Whereas the composite load on a system bus consists of large number of individual loads having different responses to system operating conditions and disturbances. The proper load modelling is, therefore, important for achieving accurate system study results.

A precise short-term power/load forecasting is essentially for monitoring and controlling power system operation. The hourly load forecast with leading time up to one week in advance is necessary for on-line solution of scheduling problems. A 24-hours load forecast is needed for successful operation of a power system. One-hour forecast is important for on-line real time control and security evaluation of a large power system. System load forecasting is an essential operation in power system control centres. Short-term load forecasting (STLF) is one of the most important procedures in the real-time control of power generation and efficient energy management systems. It is used for establishing the power station operation plan and the unit operation plan, together with generation and spinning reserve planning of energy exchange. In other words, the optimal utilization of generators and power stations is completely dependent upon the accuracy of load forecasting.

The time interval of load forecasts varies from few seconds to few minutes (very short term), half to few hours (short term), few days to few weeks (medium term) or few month to a few years (long term forecasts). Very short and short-term

forecasts are normally used for real time control actions such as security control and load despatch etc. In load prediction, weather has an important impact and needs its modelling with system load. The features that can be taken into account as input causal factors in the short term forecasting problem are as follows:

1. Temperature of the current hour
2. Average temperature of the previous day
3. Maximum temperature of the current day
4. Minimum temperature of the current day
5. Wind velocity
6. Rain for the past 3 hours
7. Rain for the past 24 hours
8. Sky condition indicator
9. Day of the week indicator
10. Wet or dry day
11. Current hour.

It is generally observed in any electric load utility that all the parameters are not recorded, so it is not physically possible to include all these in the prediction. Therefore, the more important ones are included such as day of the week, hour of the day and the previous hour of the day and the previous hours data etc.

In fact, the varying nature of load is random and load prediction requires the modelling of time series representing these variations. Since it is difficult to evolve a clear cut mathematical model for these random variables, the conventional methods

are unable to provide accurate results apart from meeting the speed requirement. To overcome this difficulty, ANN based models are suggested.

2.7.1 Neural Network Model for STLF Using Standard BPA.

2.7.1.1 Statistical Analysis of data:

Statistical analysis of data is the primary step needed in case of training the system with every feature of the data so as to make network to catch up with the trend of the data. The data analysis reveals that load variation in all the days of the week follows similar trend except for some small disturbances. The load has the lowest of its peak for the first hour of the day to sixth-seventh hour of the day and then it raises to its peak by the ninth hour of the day. The peak is almost maintained till the twenty first hour of the day and then falling to its lowest value. One day data variation is shown in Fig. 2.10. The data analysis gives the intuition that at least three past histories of the same day is required for catching up the trend of the day. It is also required to take into seasonal effects by considering the same hour load of previous one, two or three weeks. The data that is provided to the system is not having the information of the temperature. The effect of the temperature is considered by the past histories of the day and the seasonal effect with the help of past week histories. The temperature information will give prediction if there are abnormal changes within one or two hours. Therefore, compromise is made in between the data available and the accuracy wanted.

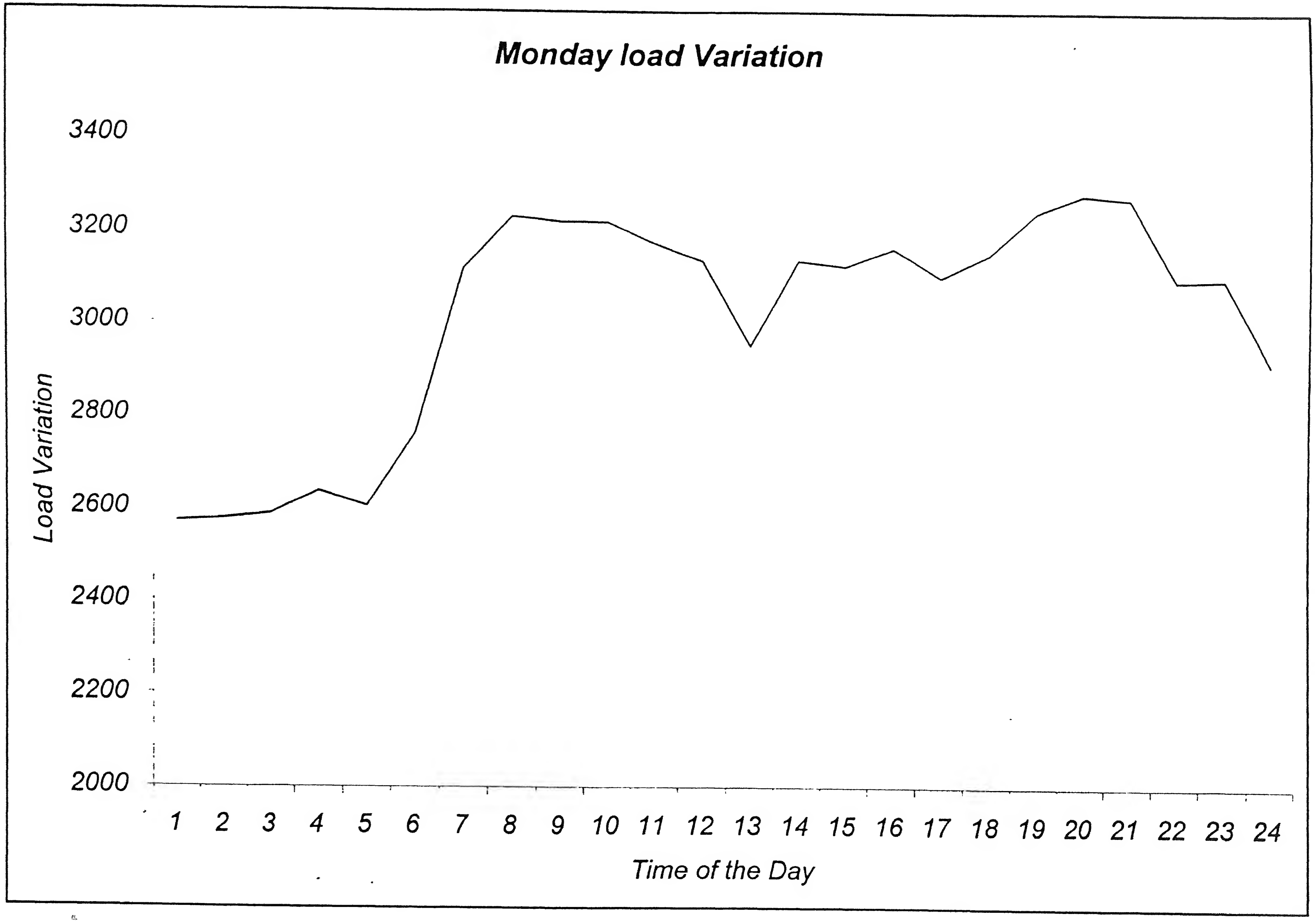

Monday load Variation
3400
3200
3000
2800
2600
2400
2200
2000
Load Variation
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Time of the Day

FIG. 2.10:

2.7.2. Approach Towards Problem:

After the analysis of data, it is decided that the prediction requires data of three past hours and three past weeks of at that hour. Various inputs to the ANN are as follows:

1. One hour past load
2. Two hour past load
3. Three hour past load
4. One week past load of the same present hour at we have to predict load
5. Two week past load of the same hour
6. Three week past load of the same hour.
7.

2.7.3. Results

The standard BPA approach has been applied to forecast the hourly electric load demands. The ANN multilayer structure has been trained using the back propagation technique, and got the following results as illustrated in Table (1). We studied 15 cases for various activation function (threshold) applied to the hidden layers and the output layers.

For 3-layer neural networks the predicted results for the best training is found by applying activation function 'sine' to hidden layer and 'logistic to output layer, as shown in figure 2.11. And the best prediction is found by applying activation function 'tanh15' to hidden layer and 'logistic' to output layer as shown in Fig 2.12.

TABLE (1) : SUMMARY OF STANDARD BACK-PROPAGATION NEURAL NETWORK RESULTS FOR STLF

Case No.	Activation Function to		3 LAYER NETWORK (6-18-1)				4-LAYER NETWORK (6-9-9-1)				5 LAYER NETWORK (6-6-6-6-1)			
	Hidden layer(s)	Output layer	Training		Prediction		Training		Prediction		Training		Prediction	
			R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r
1	Logistic	Linear	0.8574	0.926	0.7795	0.884	0.8483	0.922	0.7726	0.88	0.874	0.936	0.7582	0.878
2	Logistic	Logistic	0.8745	0.935	0.7785	0.883	0.8731	0.935	0.7832	0.885	0.8471	0.921	0.7905	0.889
3	Linear	Linear	0.7803	0.889	0.7094	0.844	0.856	0.928	0.7735	0.881	0.8561	0.929	0.768	0.879
4	Gaussian	Linear	0.8693	0.933	0.773	0.88	0.8522	0.923	0.7683	0.878	0.8943	0.946	0.7663	0.876
5	Gaussian	Logistic	0.8571	0.928	0.7714	0.879	0.8501	0.923	0.763	0.875	0.8943	0.946	0.7663	0.876
6	Tanh	Linear	0.8483	0.921	0.7597	0.872	0.8754	0.938	0.7711	0.884	0.883	0.94	0.7891	0.889
7	Tanh	Logistic	0.8509	0.928	0.75	0.872	0.9052	0.953	0.7969	0.896	0.8759	0.936	0.7676	0.877
8	Sine	Linear	0.851	0.929	0.7572	0.878	0.8561	0.927	0.7791	0.884	0.8815	0.941	0.7674	0.881
9	Sine	Logistic	0.883	0.94	0.7784	0.883	0.878	0.937	0.7797	0.884	0.8904	0.944	0.7953	0.893
10	Tanh15	Linear	0.8769	0.938	0.7592	0.876	0.8851	0.941	0.7844	0.886	0.8851	0.941	0.7844	0.886
11	Tan15h	Logistic	0.8458	0.921	0.7815	0.89	0.8813	0.939	0.753	0.868	0.8807	0.839	0.7676	0.878
12	Sym. Log.	Linear	0.874	0.935	0.7688	0.877	0.8886	0.943	0.7838	0.886	0.8895	0.943	0.7631	0.876
13	Sym. Log.	Logistic	0.4212	0.90	0.3658	0.853	0.8774	0.937	0.7673	0.876	0.8715	0.936	0.7856	0.888
14	Gau. Com.	Linear	0.8638	0.930	0.7721	0.879	0.8926	0.945	0.7845	0.888	0.8913	0.944	0.7633	0.876
15	Gau. com.	Logistic	0.8557	0.926	0.7608	0.873	0.8891	0.943	0.7755	0.881	0.8715	0.934	0.7732	0.879

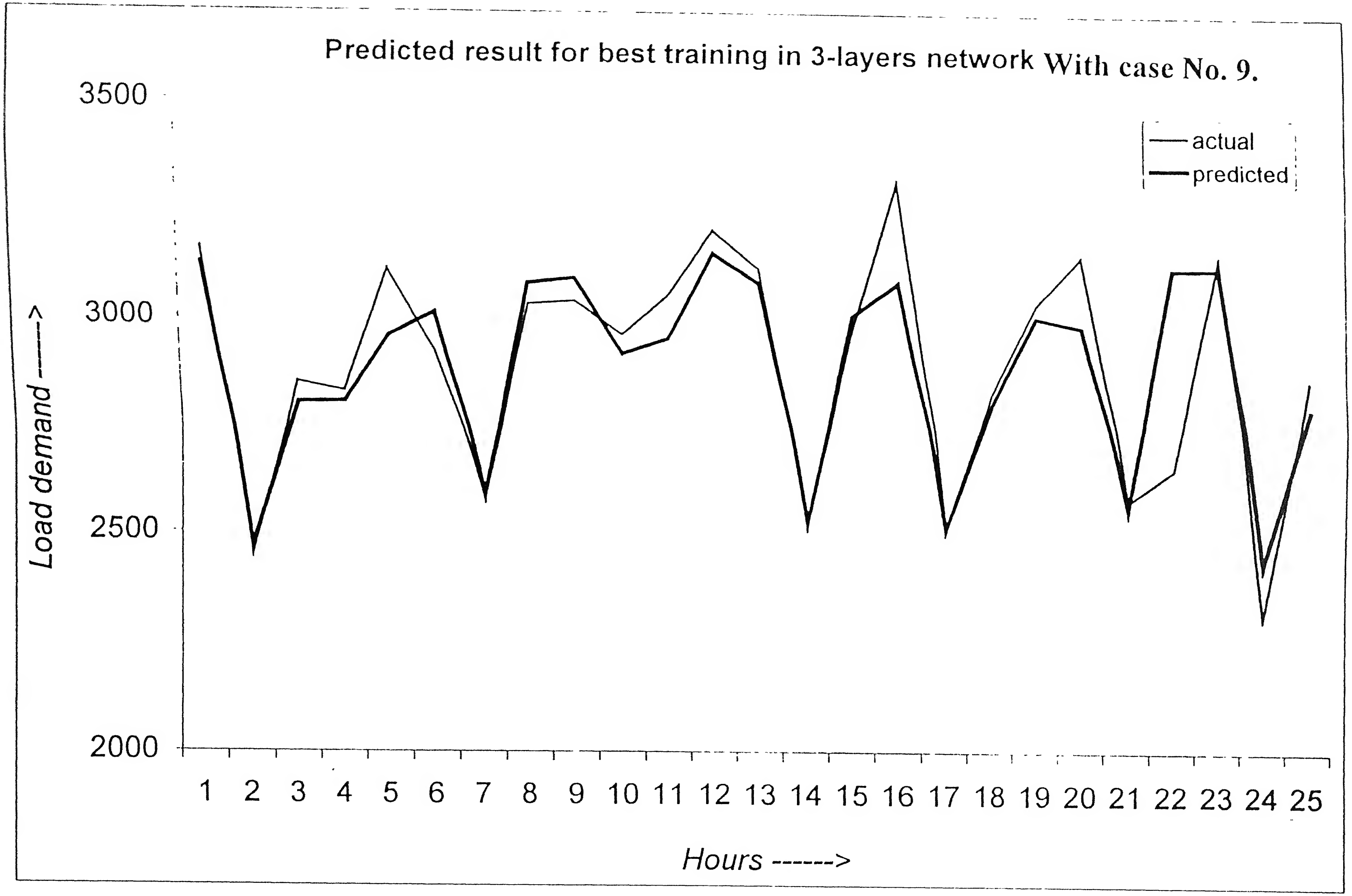
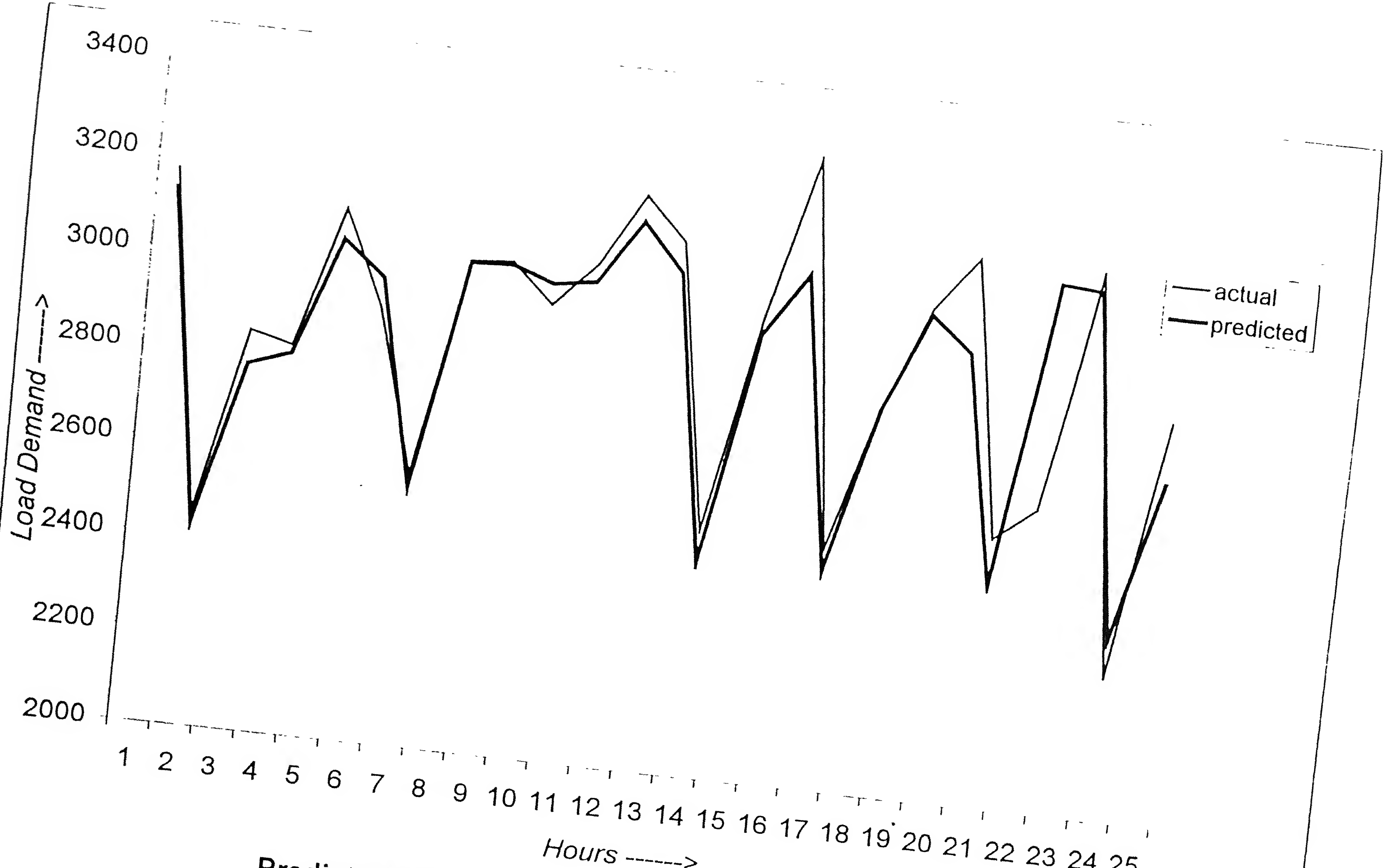
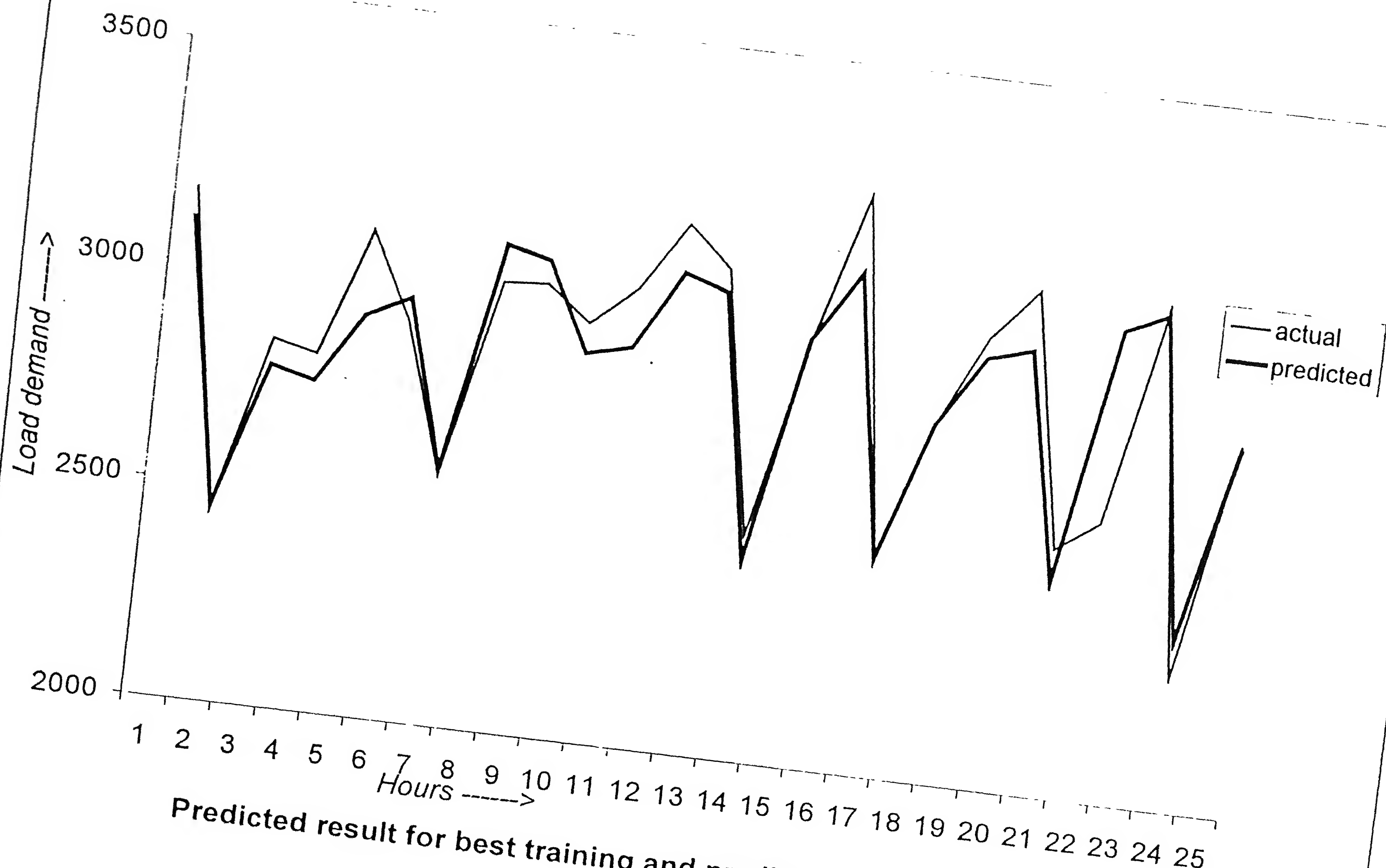

Predicted result for best training in 3-layers network With case No. 9.
3500
3000
2500
2000
Load demand ------>
actual
predicted
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
Hours ------>

Fig. 2.11



Predicted result for best prediction in 3-layer network With case No. 11.

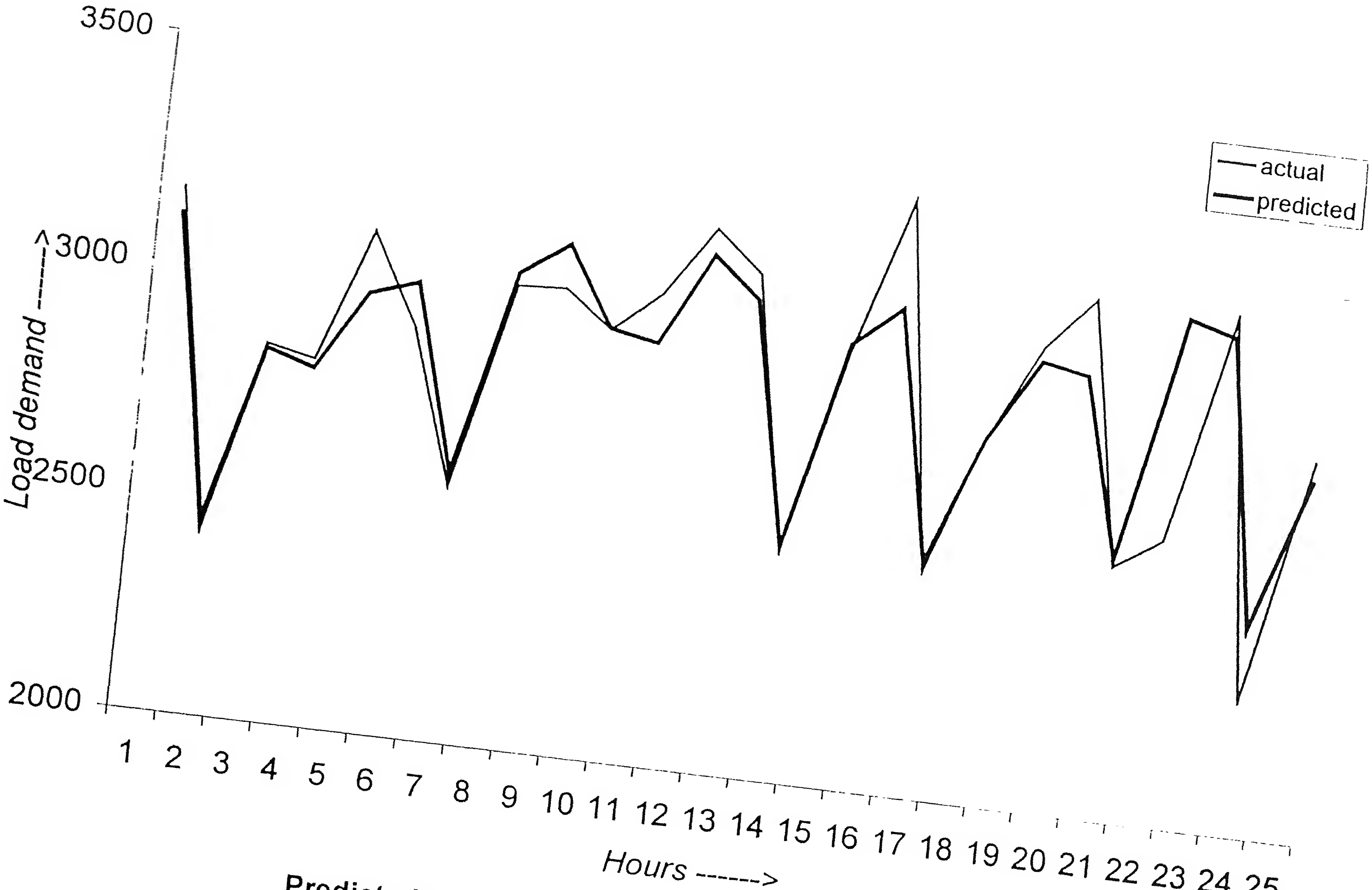
Fig. 2.12



Predicted result for best training and prediction in 4-layers network

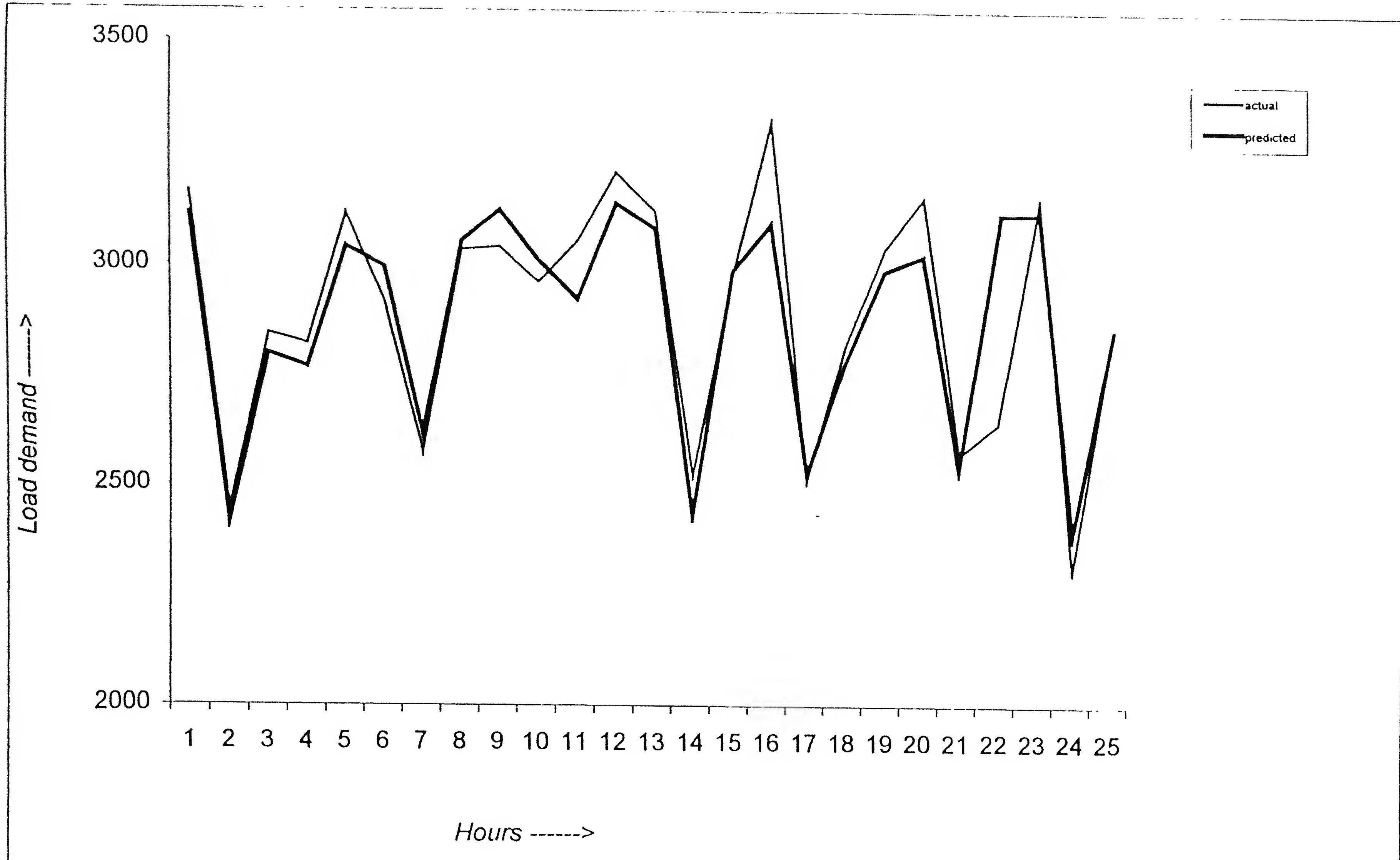
With case No. 7.

Fig. 2.13



Predicted result for best training in 5-layers network With case No. 5.

Fig. 2.14



Predicted result for best prediction in 5-layer network With case No. 9.

Fig. 2.15

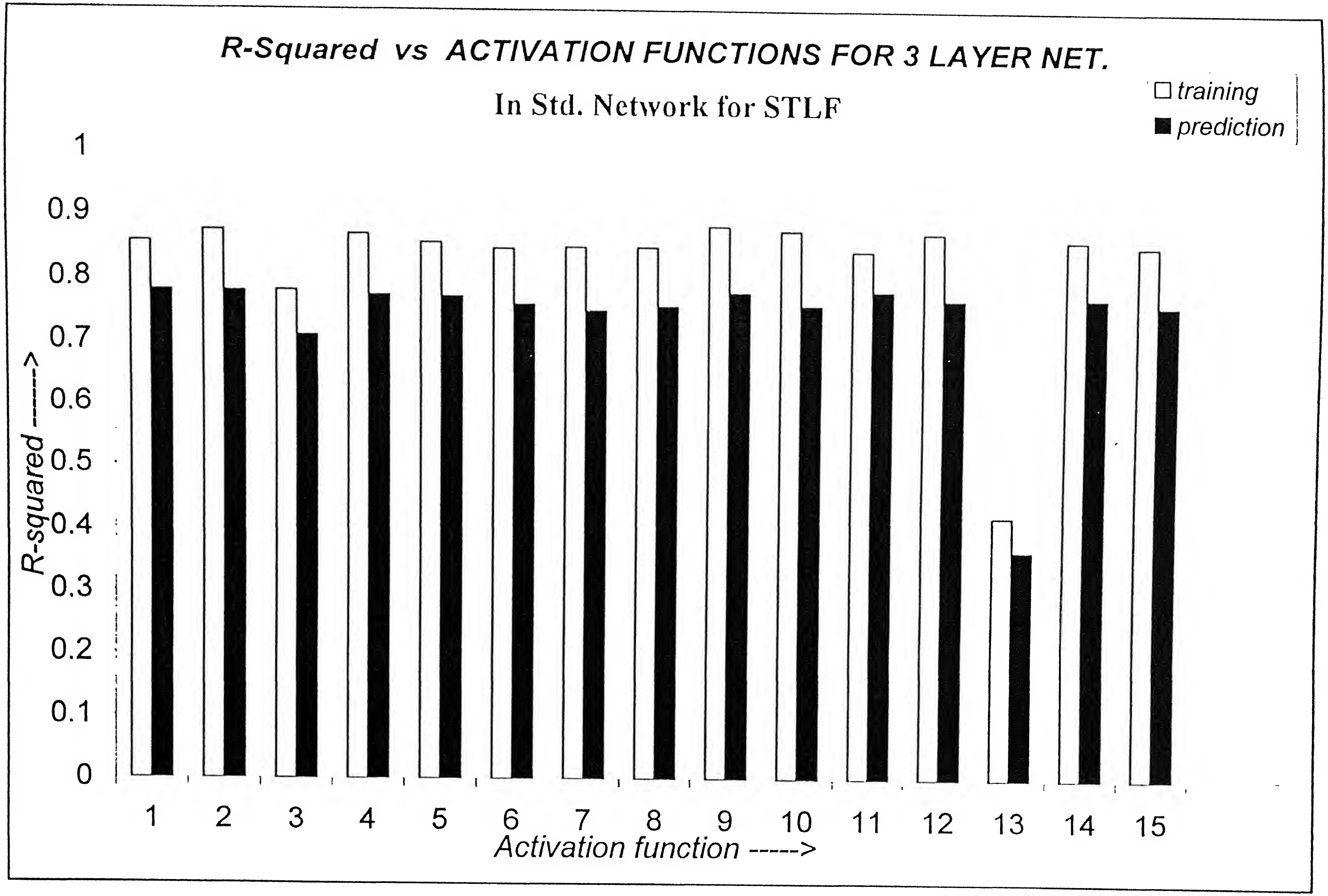

R-Squared vs ACTIVATION FUNCTIONS FOR 3 LAYER NET.
In Std. Network for STLF
training
prediction
R-squared ----->
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
Activation function ----->

Fig. 2.16

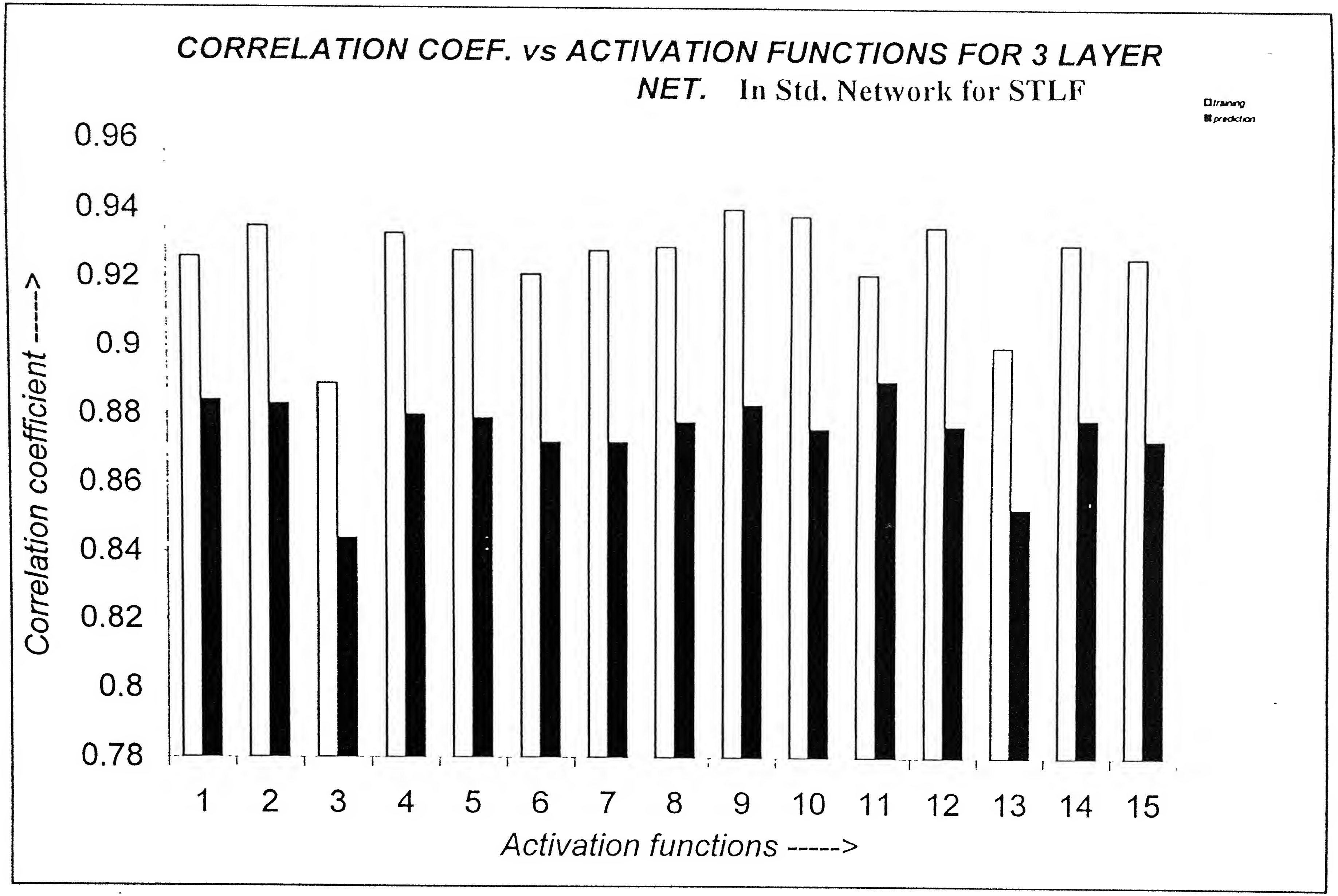

CORRELATION COEF. vs ACTIVATION FUNCTIONS FOR 3 LAYER NET. In Std. Network for STLF
training
prediction
0.96
0.94
0.92
0.9
0.88
0.86
0.84
0.82
0.8
0.78
Correlation coefficient ----->
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
Activation functions ----->

Fig. 2.17

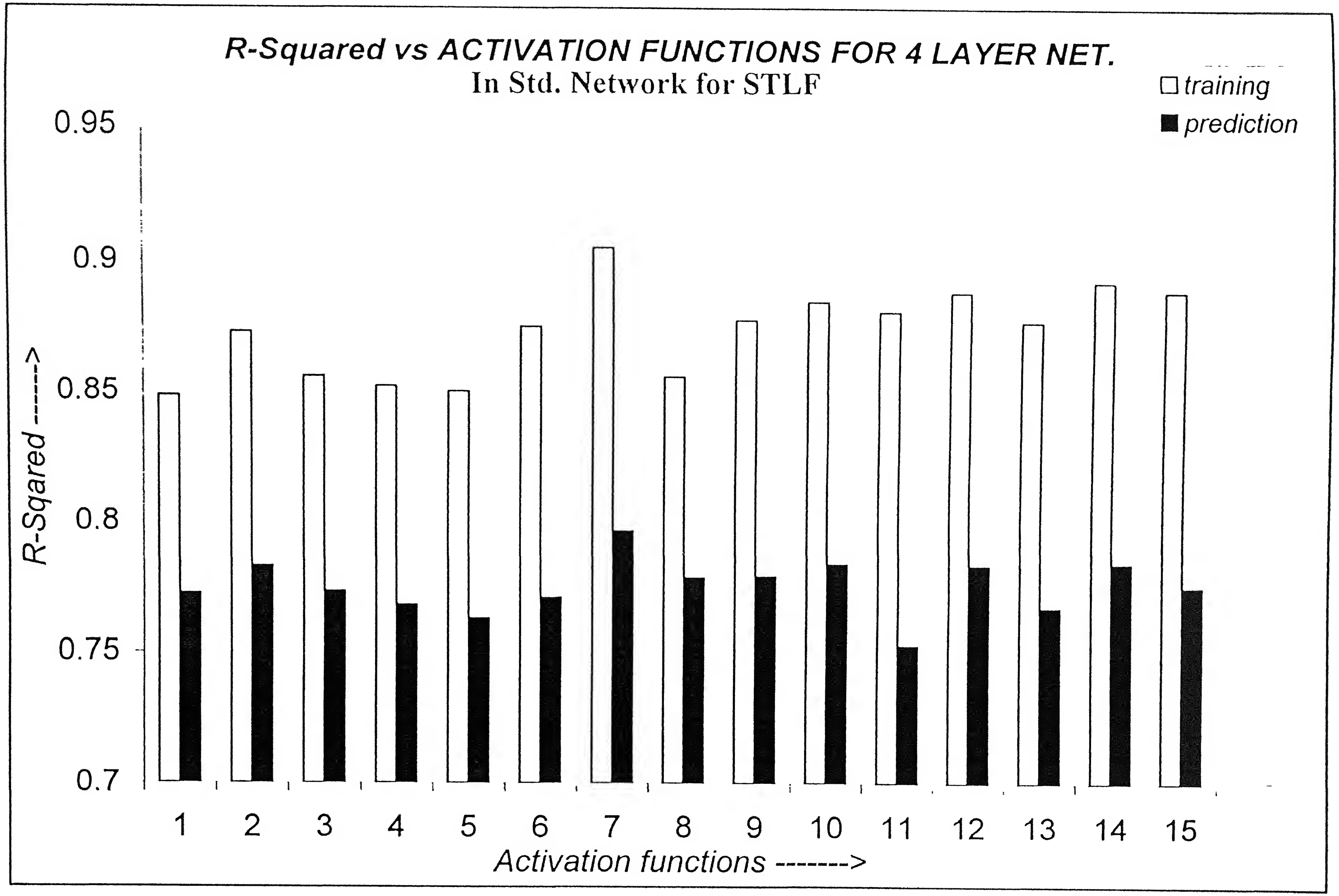

R-Squared vs ACTIVATION FUNCTIONS FOR 4 LAYER NET.
In Std. Network for STLF
training
prediction
0.95
0.9
0.85
0.8
0.75
0.7
R-Sqared ------>
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
Activation functions ------->

Fig. 2.18

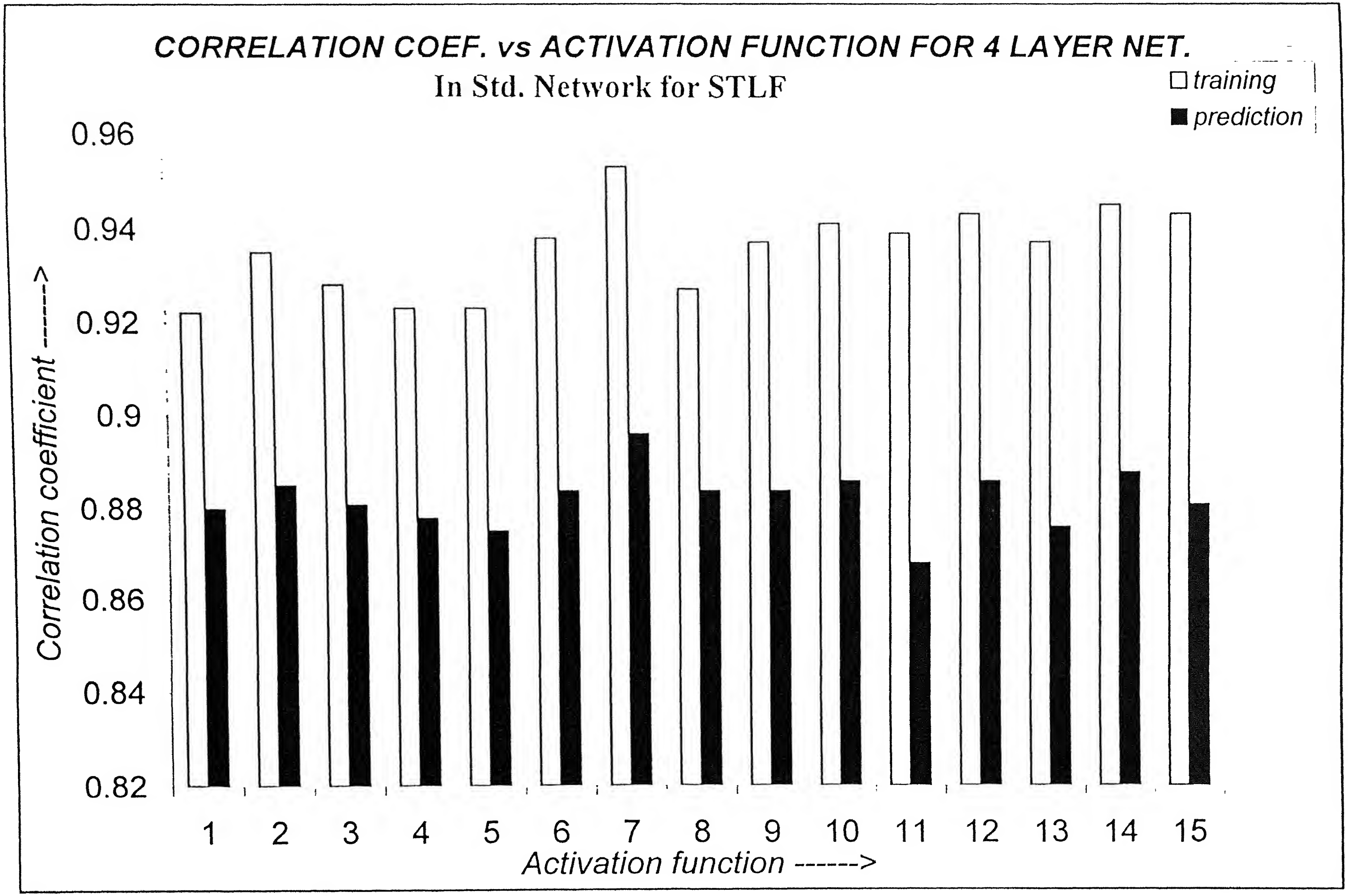

CORRELATION COEF. vs ACTIVATION FUNCTION FOR 4 LAYER NET.
In Std. Network for STLF
training
prediction
0.96
0.94
0.92
0.9
0.88
0.86
0.84
0.82
Correlation coefficient ------>
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
Activation function ------>

Fig. 2.19

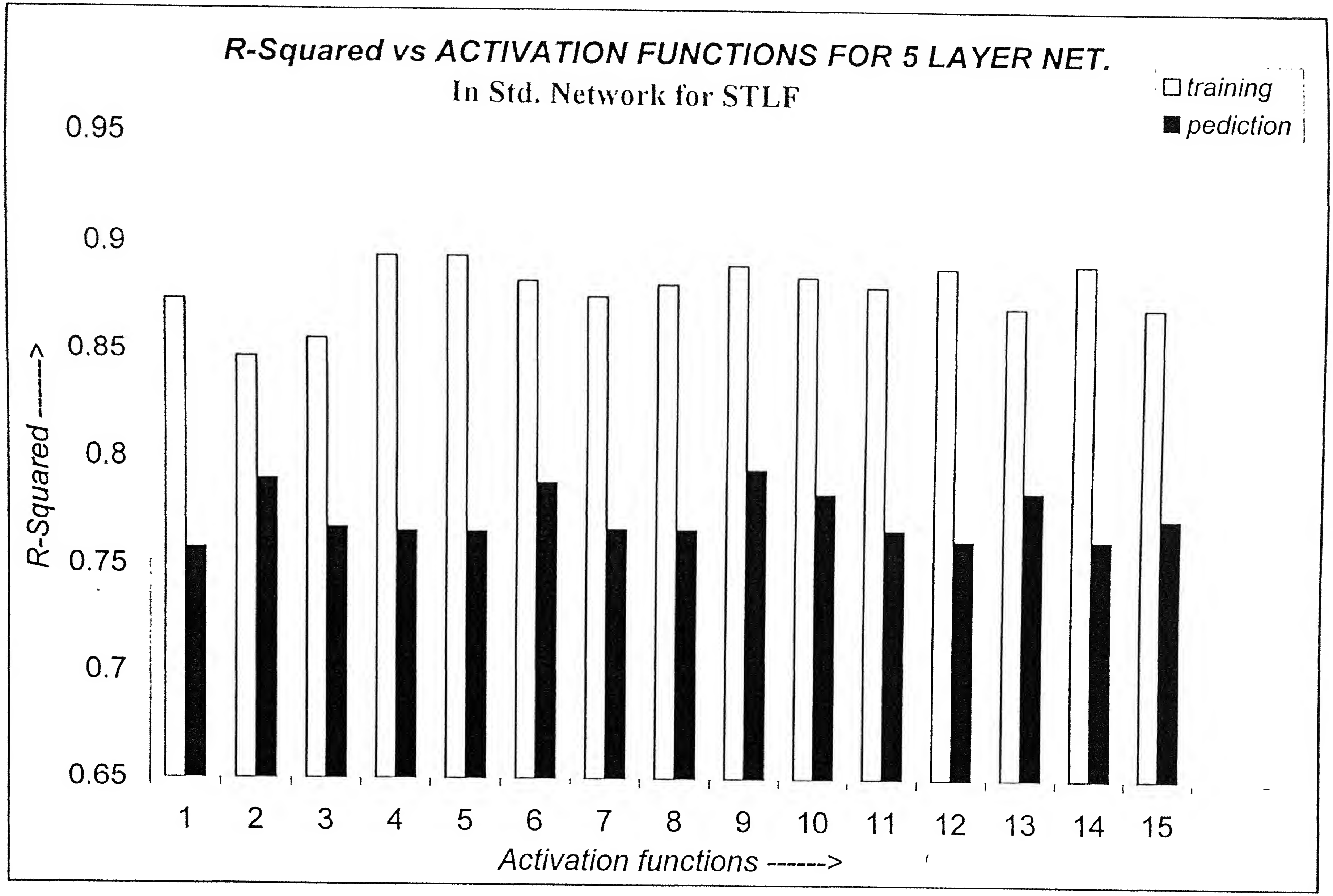

R-Squared vs ACTIVATION FUNCTIONS FOR 5 LAYER NET.
In Std. Network for STLF
training
pediction
0.95
0.9
0.85
0.8
0.75
0.7
0.65
R-Squared ------>
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
Activation functions ------>

Fig. 2.20

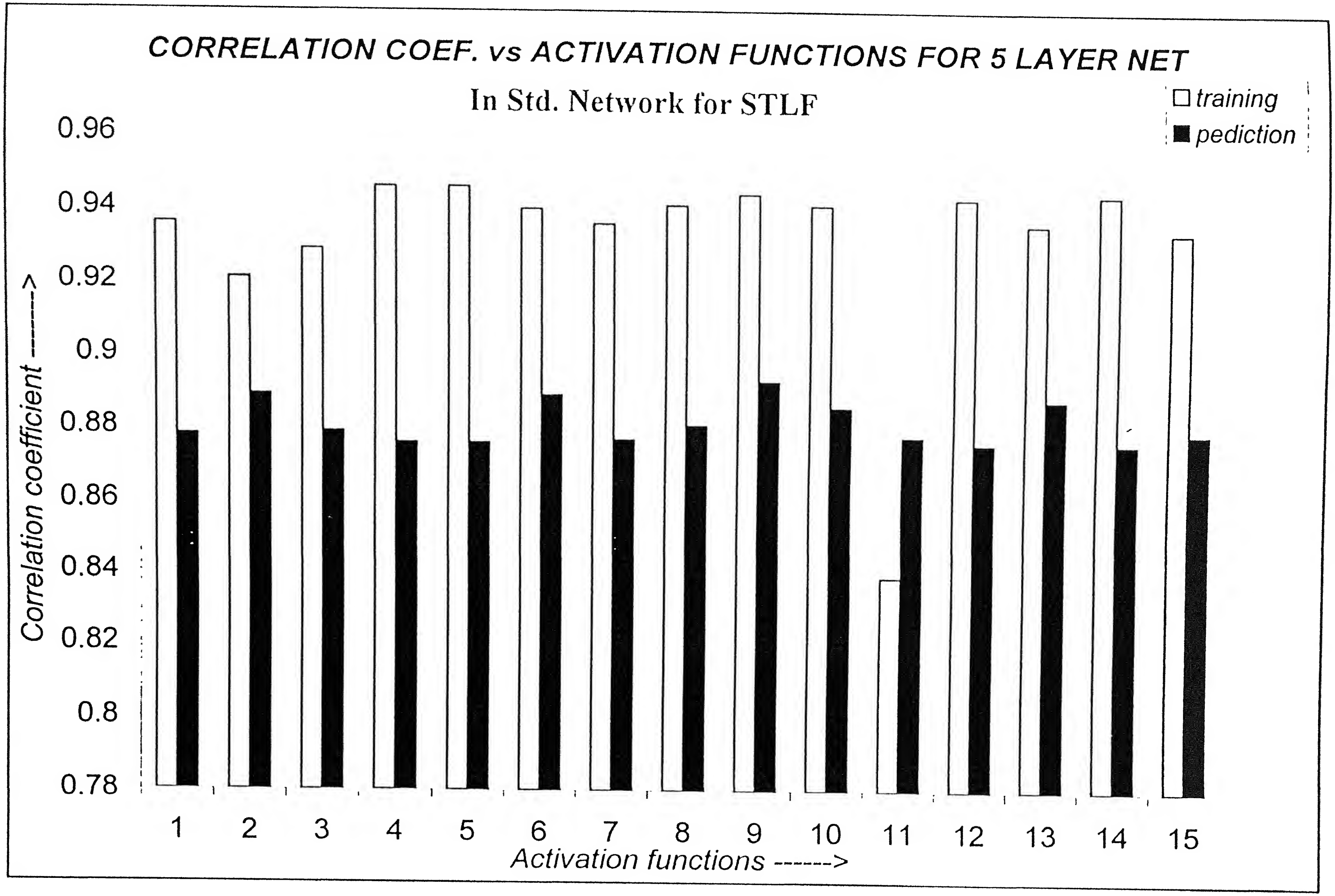

CORRELATION COEF. vs ACTIVATION FUNCTIONS FOR 5 LAYER NET
In Std. Network for STLF
training
pediction
0.96
0.94
0.92
0.9
0.88
0.86
0.84
0.82
0.8
0.78
Correlation coefficient ------->
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
Activation functions ------>

Fig. 2.21

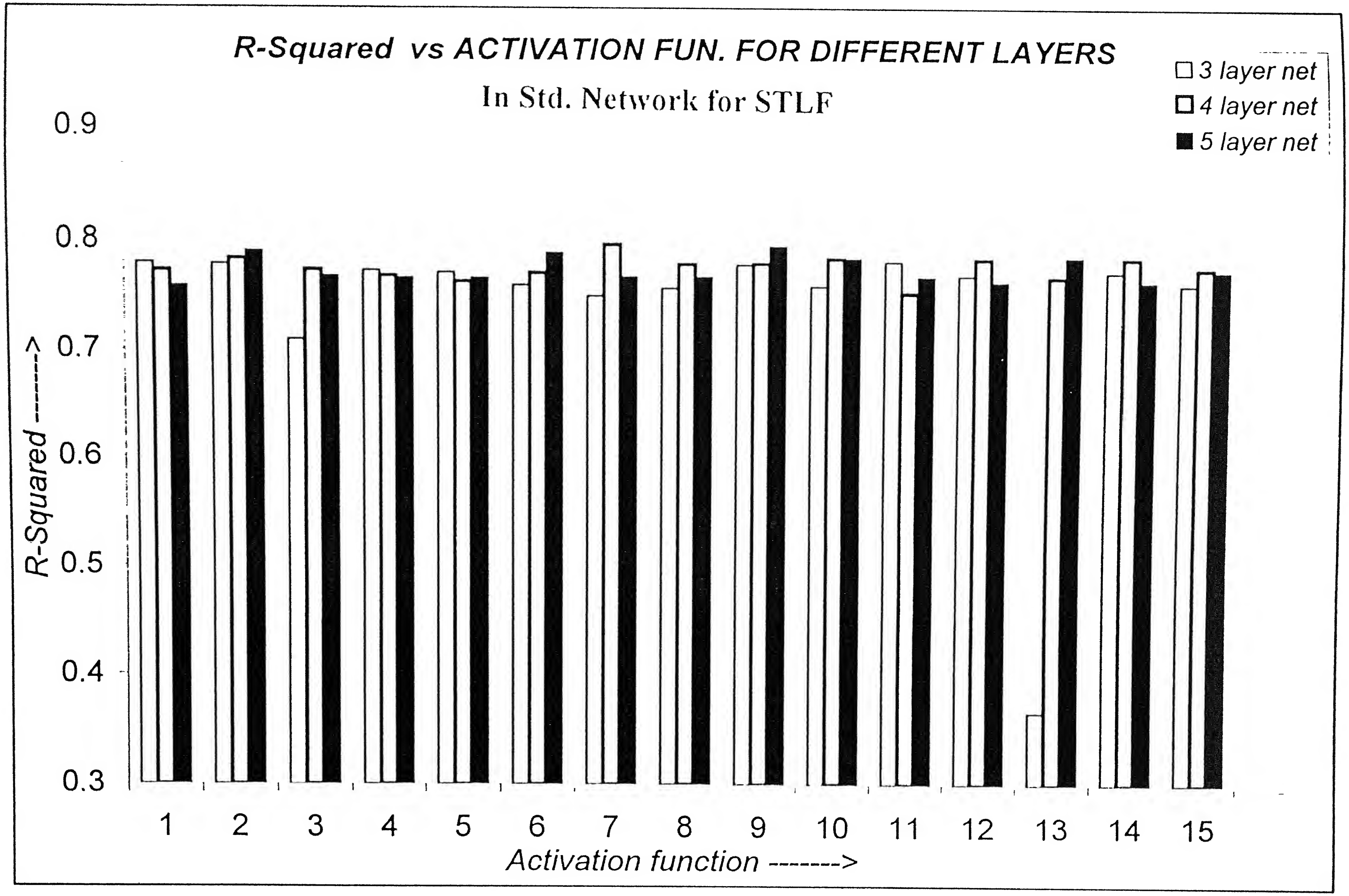

R-Squared vs ACTIVATION FUN. FOR DIFFERENT LAYERS
In Std. Network for STLF
3 layer net
4 layer net
5 layer net
0.9
0.8
0.7
0.6
0.5
0.4
0.3
R-Squared ------->
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
Activation function ------->

Fig. 2.22

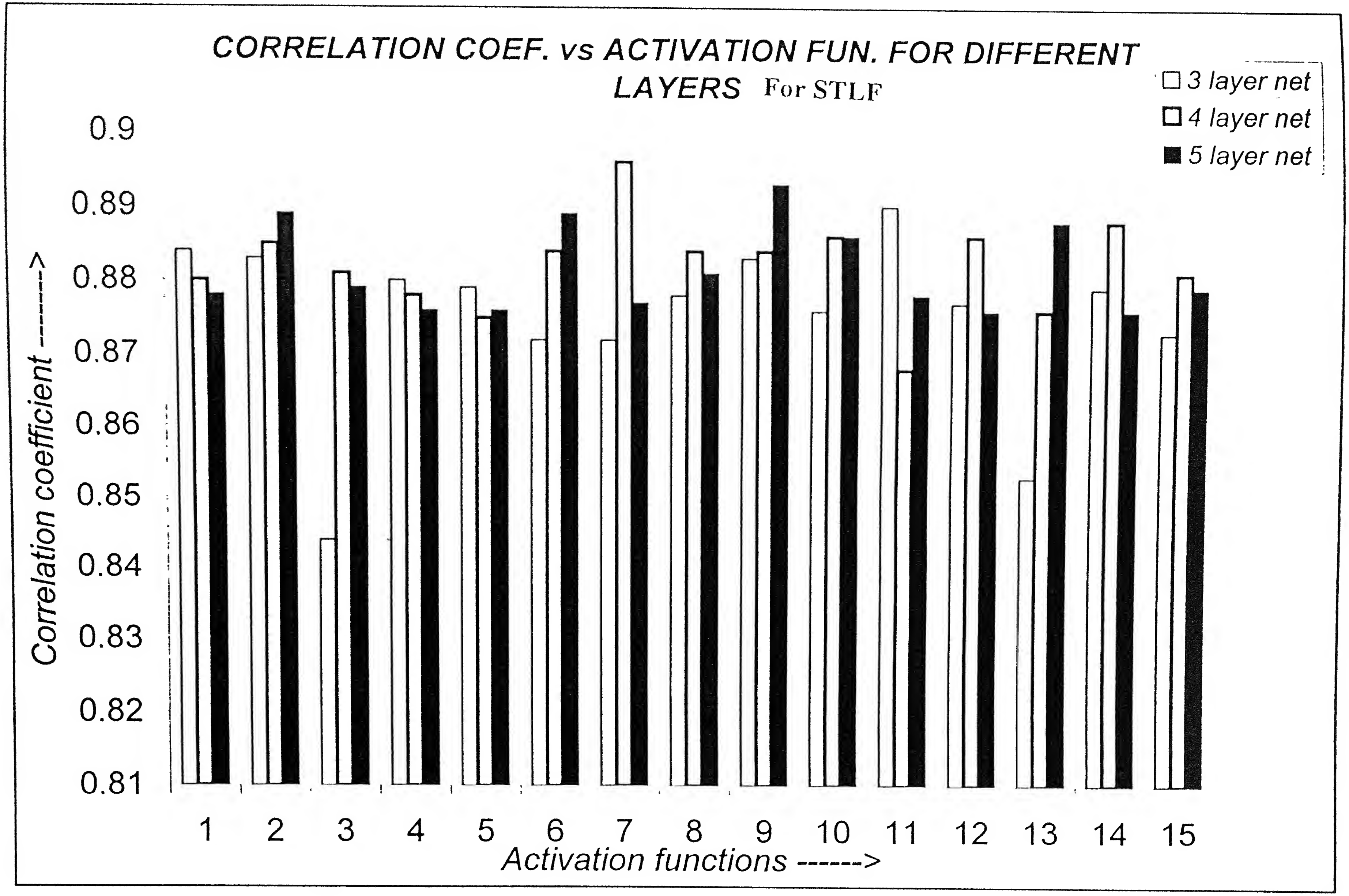

CORRELATION COEF. vs ACTIVATION FUN. FOR DIFFERENT LAYERS For STLF
3 layer net
4 layer net
5 layer net
Correlation coefficient ------>
0.9
0.89
0.88
0.87
0.86
0.85
0.84
0.83
0.82
0.81
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
Activation functions ------>

Fig. 2.23

For 4-layer neural network the predicted results for both the best training and best prediction are found by applying activation function 'tanh' to the hidden layers and 'logistic to the output layer as shown in Fig 2.13.

For 5-layer neural network the predicted results for best training is found by applying threshold 'Gaussian' to the hidden layers and 'logistic to the output layer as shown in figure 2.14, and for the best prediction is found by applying threshold 'sine' to the hidden layers and 'logistic' to the output layer as shown in Fig 2.15.

2.8. Financial Forecasting for Interest Rate Prediction.

The approach discussed for STLF for building neural network is applied for prediction of interest rates. We can take any financial time series process. For this, we have chosen interest rates, as represented here by the rates for 91- day Treasury bills, or so called T-bill, are quite volatile and non-linear, data are taken from [15] as shown in appendix.

2.8.1. Modelling of Interest Rates: --

Interest rate is modelled based on an example from an article by Larrain (1991)[7]. According to Larrain, following five factors account for roughly 90% of the variation in interest rates: --

(1) Previous interest rates (or T-bill rates),

(2) Real Gross National Product (GNP),

(3) Consumer Price Index (CPI),

(4) M2 nominal money supply (all cash in circulation and deposits in savings and checking accounts),

(5) Personal Wealth (difference between personal income and personal consumption).

The basic data files contain over 20 years worth of quarterly data. In this problem not only the past history but also the above mentioned all the factors are considered.

The system is modelled to take into account the data of past 20 years from 1966 to 1985, i.e. 80 quarters of data points two more data points for the test file. The following combinations for pattern files have been taken: --

(1). The GNP & Interest Rates inputs use, the basic data set starts with the first quarter of 1966,

(2). CPI is to be delayed by one quarter relative to interest rates data, i.e., its starting point is the fourth quarter of 1965,

(3). M2 money supply, and Personal Wealth data are delayed by two quarters relative to interest rates data and hence started with the third quarter of 1965,

(4). Since we wanted to model the next quarter's interest rate, hence we started the output interest rates one quarter later, i.e., the second quarter of 1966.

The results of ANN modelling are shown in Figure 2.1. It is clear from the figure 2.24 that Neural Network is capable of modelling all of the non-linear fluctuations.

2.8.2. Predicting Interest Rate:

The fundamental financial market characteristics change over a period of four to five years (Peters 1991) [7]. That is, the market "forgets" the influence of data that is more than five years old. For this reason, five-year data window i.e., each training set (window) contains 20 data points since we are taking quarterly data, are used in our problem. We look at 15 data windows, starting years being 1967 to 1981 and

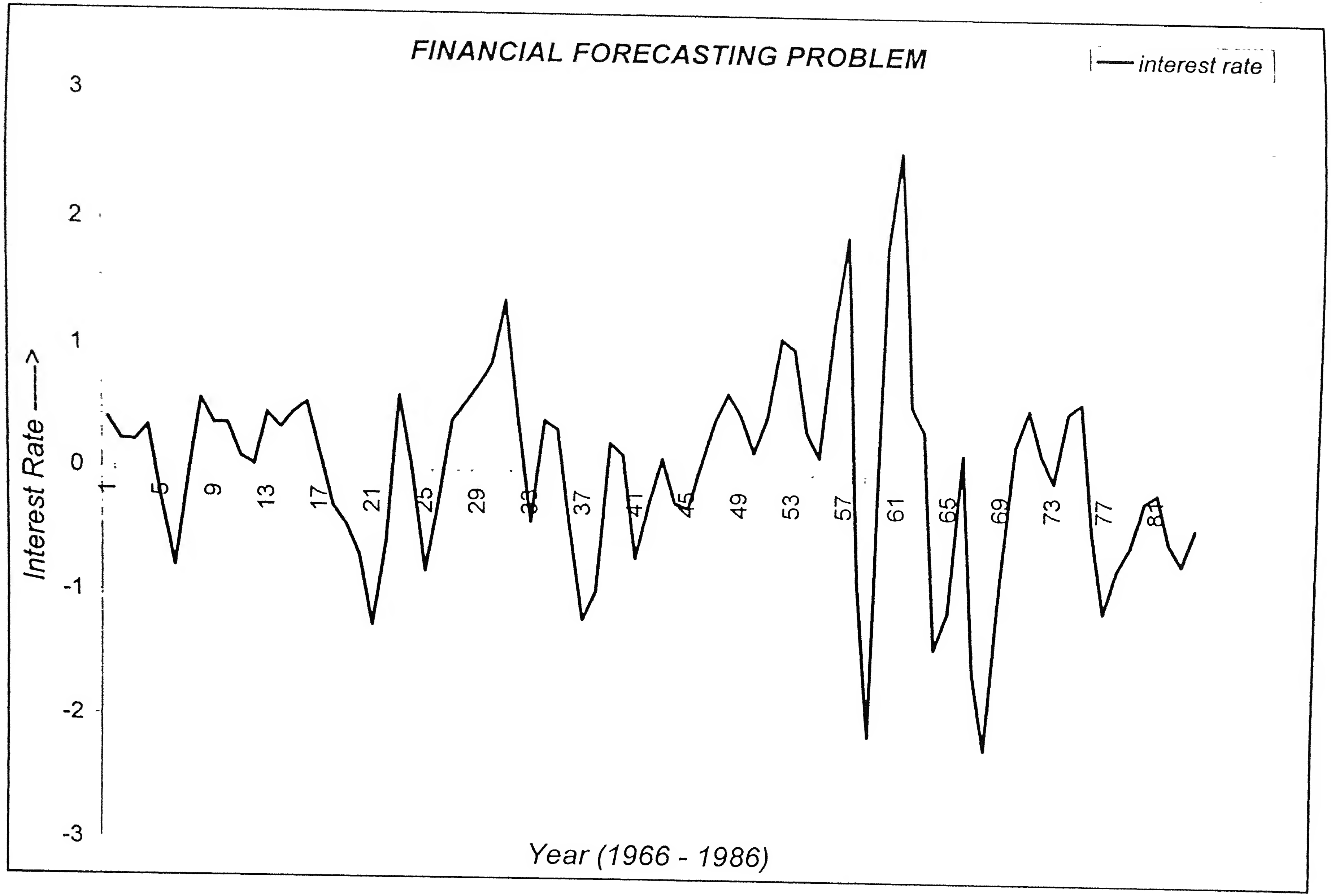

FINANCIAL FORECASTING PROBLEM
interest rate
3
2
1
0
-1
-2
-3
Interest Rate ---->
1
5
9
13
17
21
25
29
33
37
41
45
49
53
57
61
65
69
73
77
81
Year (1966 - 1986)

Fig.2.24

ending years being 1971 to 1985 Each training set had 20 data points and the test set has two more data points. i.e.. the prediction testing of the first as well as the second quarter of a next year immediately following the training data. Hence 15 patterns files (windows) has selected are given in Appendix. In which each patterns file contain 22 patterns whereas first 20 sets are for training set and last 2 set for test set which we have to predict through the training network which is trained by training set.

2.8.3. Results.

The standard BPA approach has been applied to forecast the interest rate. The neural network is trained by taking only window-1 patterns-data, and results are illustrated in Table (2). We studied 15 cases for various activation function (threshold) applied to the hidden layers and the output layers.

For 3-layer neural network the best training result is found by applying threshold function 'tanh15' to hidden and 'linear' to the output layer but in this case the predicted result is worst as given in Table (2), where the correlation coefficient is negative one. And best prediction is found by applying threshold function 'tanh' to hidden and 'linear' to the output layer as illustrated in Table (2) and shown in figure 2.25. Similarly for 4-layer neural network the best prediction is found by applying threshold function 'symmetric logistic' to the hidden layers and 'linear' to the output layer.as shown in Fig 2.26.

For 5-layer neural network there is no best prediction result as shown in Table (2), where all cases have R-squared values is zero.

TABLE (2) : SUMMARY OF STANDARD BACK-PROPAGATION NEURAL NETWORK RESULTS FOR FINANCIAL FORECASTING

se).	Activation Function to		3 LAYER NETWORK (5-7-1)				4-LAYER NETWORK (5-4-4-1)				5 LAYER NETWORK (5-2-2-2-1)			
	Hidden layer(s)	Output layer	Training		Prediction		Training		Prediction		Training		Prediction	
			R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r
	Logistic	Linear	0.9854	0.993	0.1571	1.000	0.2392	0.649	0.000	1.00	0.000	0.491	0.000	-1 00
	Logistic	Logistic	0.4957	0.787	0.5468	1.000	0.3608	0.625	0.000	1.00	0.000	-0.492	0.000	-1.00
	Linear	Linear	0.000	0.837	0.6028	1 000	0.000	0.173	0.000	-1.00	0.000	0.000	0.000	0 000
	Gaussian	Linear	0.2629	0.716	0.4361	1.000	0.000	0.657	0.000	1.00	0.1875	0.829	0.000	1.000
	Gaussian	Logistic	0.6767	0.842	0.3658	1.000	0.9083	0.953	0.000	1.00	0.000	-0.694	0.000	-1.00
	Tanh	Linear	0.6572	0.818	0.9147	1.000	0.000	0.794	0.000	1.00	0.2424	0.567	0.000	0.000
	Tanh	Logistic	0.4095	0.802	0.4109	1.000	0.6138	0.798	0.000	0.00	0.2794	0.605	0.000	-1.00
	Sine	Linear	0.6666	0.829	0.1435	1.000	0.000	0.819	0.000	1.00	0.000	0.691	0.000	1.00
	Sine	Logistic	0.4203	0.799	0.4266	1.000	0.7864	0.897	0.000	-1.00	0.6507	0.831	0.000	1.00
0	Tanh15	Linear	1.000	1.000	0.000	-1.000	0.6184	0.802	0.000	1.00	0.000	0.693	0.000	1.00
1	Tan15h	Logistic	0.5924	0.818	0.5957	1.000	0.9029	0.953	0.000	1.00	0.3193	0.586	0.000	-1.00
2	Sym. Log.	Linear	0.6037	0.802	0.4545	1.000	0.5364	0.736	0.6106	1.00	0.3002	0.657	0.000	-1.00
3	Sym. Log.	Logistic	0.4827	0.801	0.4299	1.000	0.4645	0.814	0.000	1.00	0.000	0.735	0.000	1.00
4	Gau. Com.	Linear	0.000	0.000	0.000	0.000	0.2441	0.937	0.000	1.00	0.000	0.655	0.000	1.00
5	Gau. com.	Logistic	0.5291	0.774	0.6050	1.000	0.000	0.552	0.000	1.00	0.000	0.654	0.000	1.00

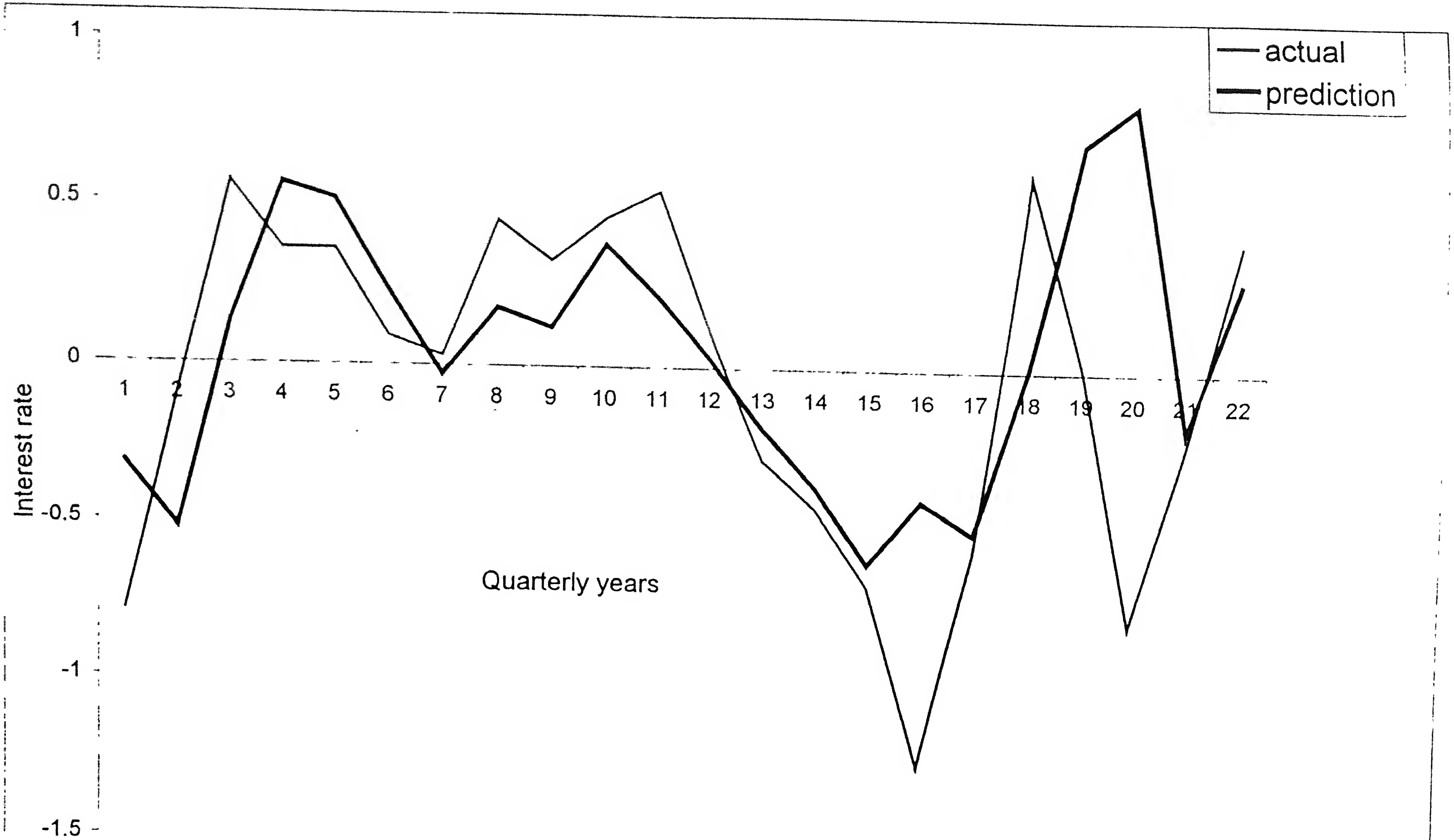


Fig. 2.25: Best Prediction of Interest Rate on 3-layer Standard Neural Network.

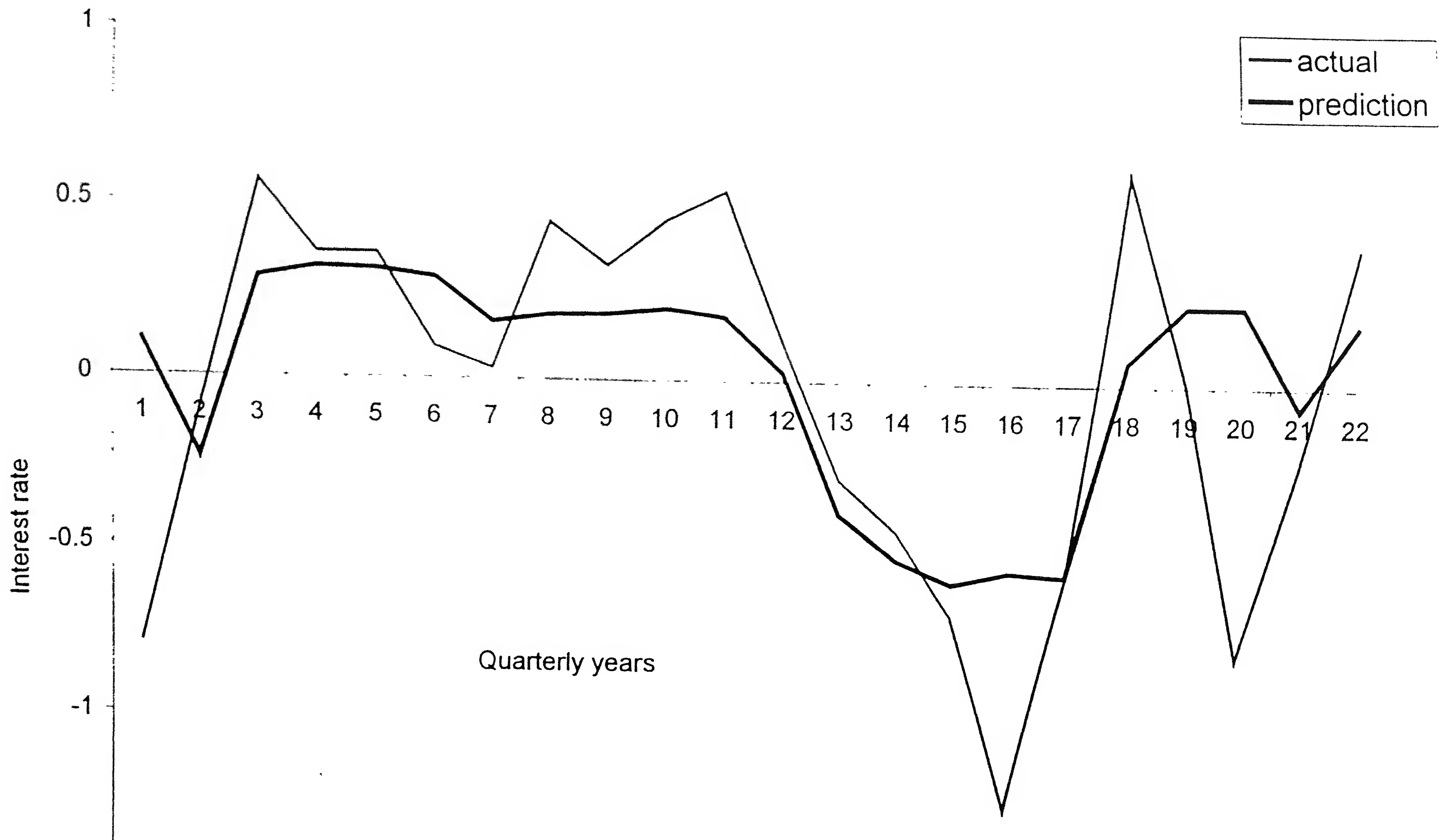


Fig. 2.26: Best prediction of interest rate on 4-layer Std. Neural Network.

2.9. Conclusion.

The best model for prediction of load demand turns out to be the 4-layer (6-9-9-1) standard back-propagation neural network, with threshold function 'tanh' in the hidden layer and 'logistic' in the output layer. And for prediction of interest rate of the financial forecasting the best model is 3-layer (6-18-1) neural network with threshold function 'tanh' in the hidden layer and 'linear' in the output layer.

Chapter 3.

Non-Conventional Neural Network Models for Prediction.

In the last chapter the standard BPA has been studied to solve two problems i.e. STLF and interest rate prediction. The major part of the study has been devoted to study the influence of the thresholding function and parameters effecting the convergence of BPA for given problems. However, it was assumed that neurons are connected among neighbouring layers only In this chapter, possibilities are explored for connecting neurons in different layers other than conventional connections i.e. Jump connections and Feedback connections etc. The comparison of mainly three types of neural networks has been carried out in the chapter. These neural networks are the following:

(1). Jump Connection Neural Networks.

(2). Recurrent Neural Networks.

(3). Ward Networks.

The above variations of ANN are applied to the problems of STLF and interest rate prediction and result is presented here.

3.1. Jump Connection Neural Networks.

This is the Back Propagation Neural Network with each layer connected to every previous layer.

(a). With 1 hidden layer as shown in figure 3.1.

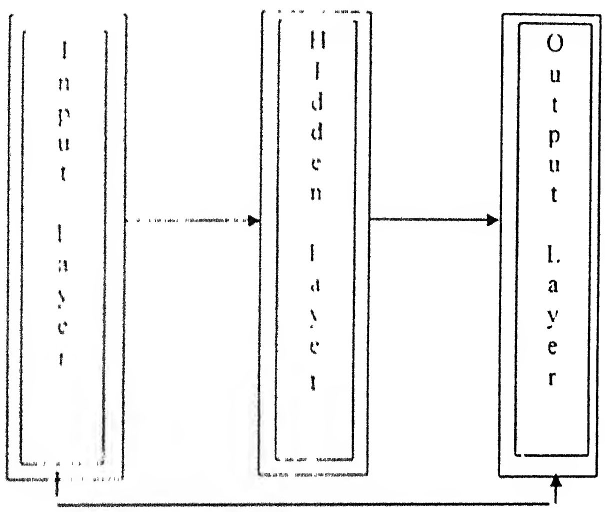


Fig 3.1: Block diagram of Jump connection with one hidden layer neural network

(b). With 2 hidden layers as shown in figure 3.2

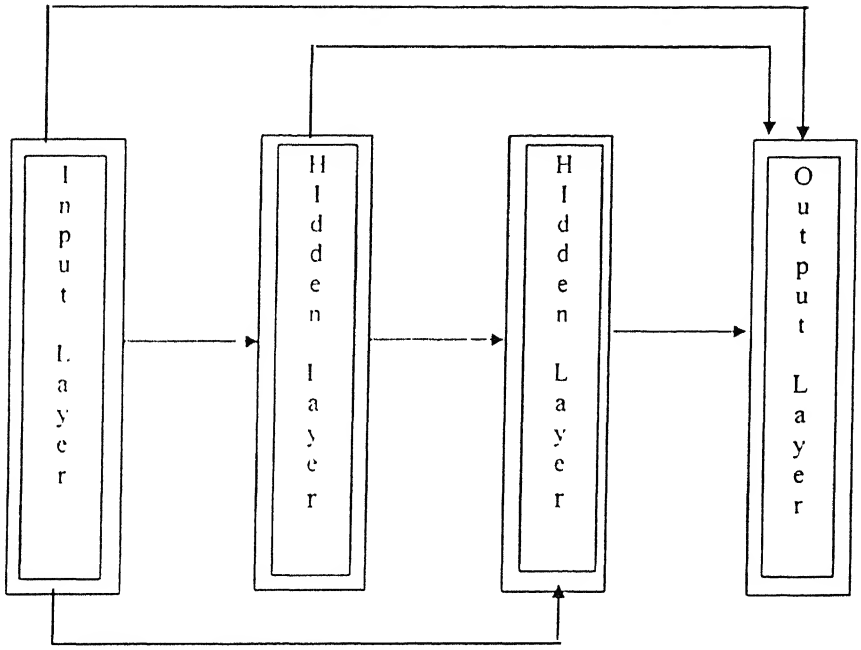


Fig 3.2: Block diagram of Jump connection with two hidden layer neural network

(c). With 3 hidden layer as shown in figure 3.3.

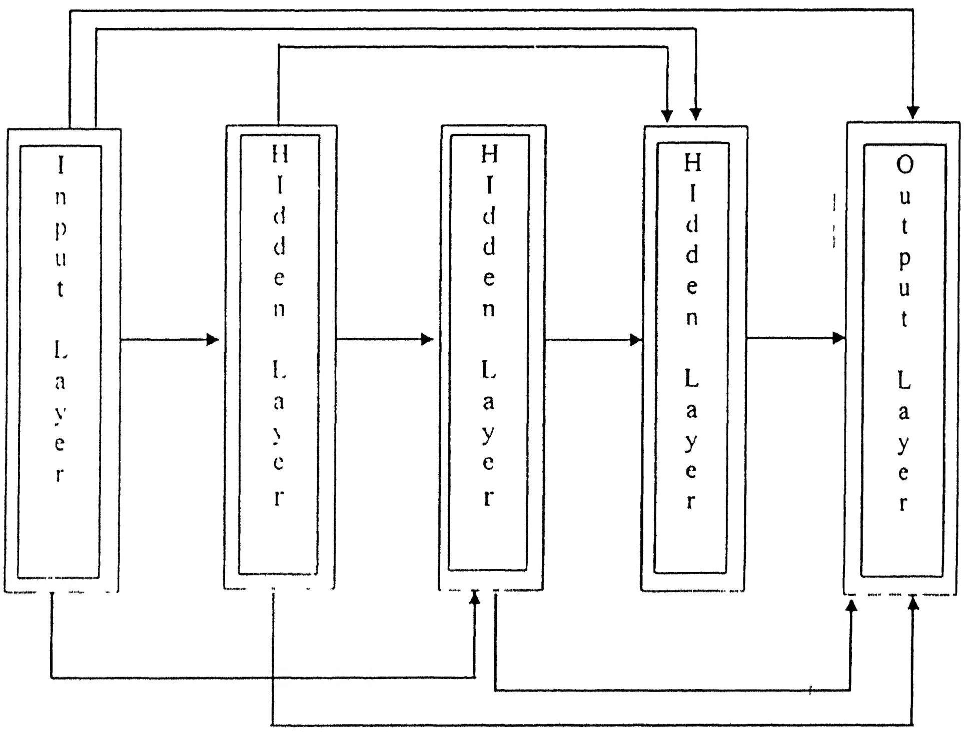


Fig 3.3: Block diagram of Jump connection with three hidden layer neural network

3.1.1. Short Term Power Demand Prediction.

3.1.1.1. Results

The best model in Jump connection neural network for STLF is 3-layer network which gives best training and prediction results compared to others as illustrated in Table (3).

In 4-layer neural network best training results is found by applying threshold function 'Gaussian compliment' to the hidden layers and 'logistic' to the output layer, but better prediction is found with threshold 'tanh15' to hidden layers and 'logistic' to the output layer.

In 5-layer neural network best training with threshold function 'sine' to hidden layers and 'linear' to the output layer, but better prediction is found with threshold function 'sine' to hidden layers and 'logistic' to the output layer.

Among the entire Jump connection neural network the best model is found 3-layer (6-18-1) with threshold function 'logistic' in hidden layer and output layer. The prediction results are shown in Fig 3.4.

3.1.2. Interest Rate Prediction.

3.1.2.1. Results

Following results are obtained on Jumpconnection neural network. In the case of interest rate prediction as illustrated in Table (4).

In 3-layer network we found the best prediction with threshold function 'Gauss comp.' to hidden layer and 'linear' to the output layer.

In 4-layer network, better training is found in case no 4 as in Table(4) where prediction is worst, and in case no.15.the prediction is better but training is worst.

TABLE (3) : SUMMARY OF JUMP CONNECTION NEURAL NETWORK RESULTS FOR STLF

Case No.	Activation Function to		3 LAYER NETWORK (6-18-1)				4-LAYER NETWORK (6-9-9-1)				5 LAYER NETWORK (6-6-6-6-1)			
	Hidden layer(s)	Output layer	Training		Prediction		Training		Prediction		Training		Prediction	
			R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r
1	Logistic	Linear	0.8734	0.935	0.4895	0.831	0.867	0.931	0.7756	0.881	0.8638	0.931	0.7689	0.879
2	Logistic	Logistic	0.8913	0.944	0.7996	0.890	0.8491	0.923	0.7760	0.881	0.8752	0.936	0.7865	0.887
3	Linear	Linear	0.5181	0.873	0.4661	0.823	0.859	0.927	0.7721	0.879	0.8658	0.930	0.7686	0.887
4	Gaussian	Linear	0.8663	0.931	0.7725	0.880	0.8859	0.911	0.7529	0.869	0.8665	0.931	0.7762	0.881
5	Gaussian	Logistic	0.8843	0.94	0.7794	0.885	0.8843	0.940	0.7794	0.885	0.8618	0.928	0.7793	0.883
6	Tanh	Linear	0.8634	0.93	0.7753	0.881	0.8779	0.937	0.7661	0.881	0.8677	0.932	0.764	0.875
7	Tanh	Logistic	0.8553	0.926	0.7757	0.882	0.8306	0.924	0.7595	0.883	0.8798	0.938	0.7686	0.877
8	Sine	Linear	0.844	0.920	0.7675	0.879	0.8182	0.917	0.7409	0.872	0.9386	0.969	0.7710	0.888
9	Sine	Logistic	0.8592	0.928	0.7775	0.882	0.8757	0.936	0.7556	0.870	0.8911	0.944	0.7945	0.892
10	Tanh15	Linear	0.8902	0.944	0.7965	0.893	0.8583	0.927	0.7647	0.875	0.8676	0.935	0.7757	0.884
11	Tan15h	Logistic	0.8531	0.925	0.7706	0.880	0.8816	0.939	0.7970	0.893	0.8622	0.929	0.7819	0.885
12	Sym. Log.	Linear	0.8238	0.91	0.7495	0.870	0.8221	0.913	0.7442	0.867	0.8943	0.946	0.7782	0.882
13	Sym. Log.	Logistic	0.8559	0.927	0.7747	0.882	0.8604	0.928	0.7785	0.883	0.8811	0.939	0.786	0.887
14	Gau. Com.	Linear	0.8601	0.927	0.7594	0.872	0.8792	0.938	0.7839	0.885	0.8644	0.930	0.7508	0.867
15	Gau. com.	Logistic	0.8541	0.925	0.7563	0.870	0.9082	0.953	0.7916	0.891	0.8546	0.926	0.7677	0.878

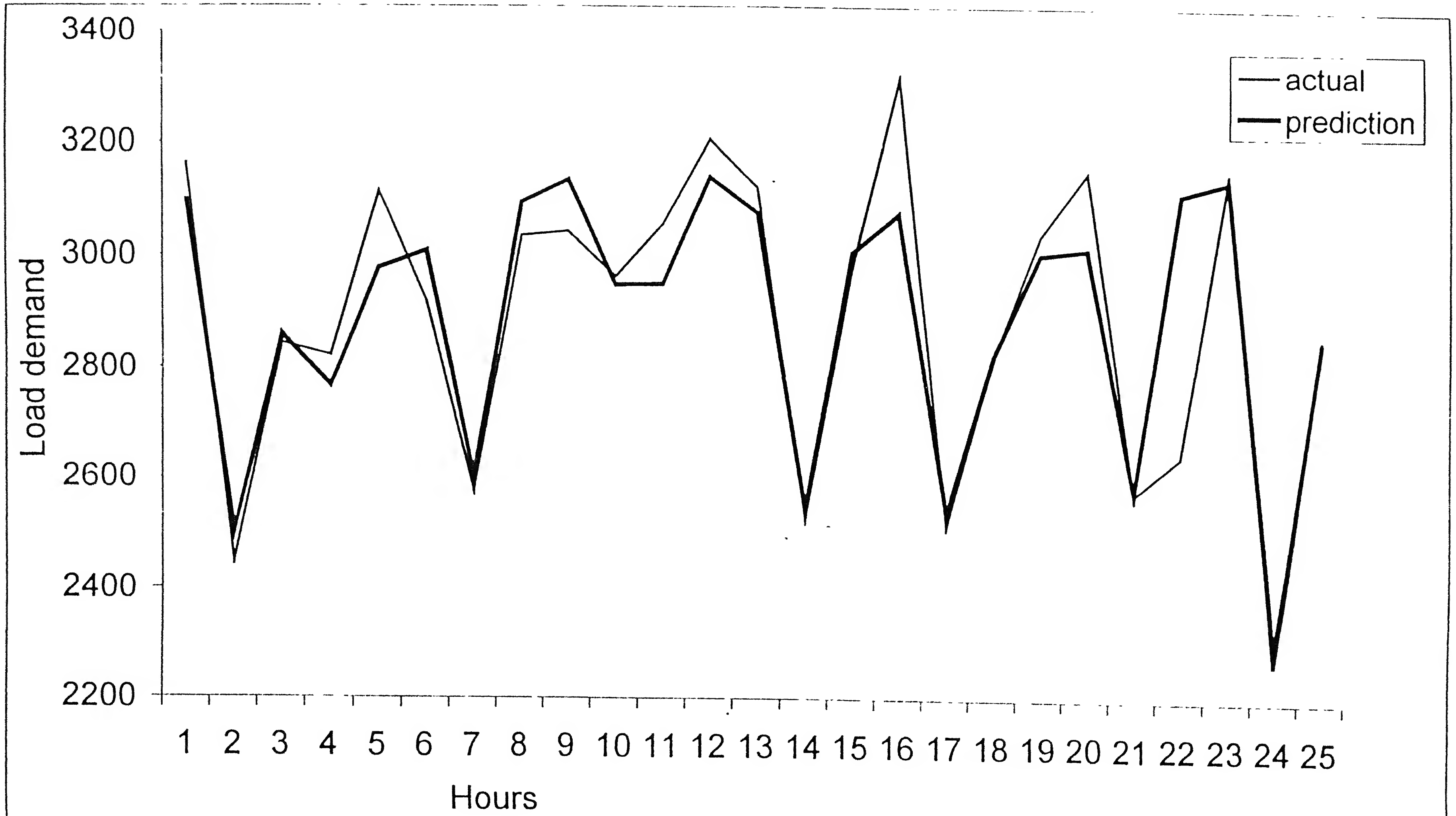


Fig.3.4: Best Prediction of STLF on 3-layer Jump Connection ANN. With case No. 2.

TABLE (4) : SUMMARY OF JUMP CONNECTION NEURAL NETWORK RESULTS FOR FINANCIAL FORECASTING

Case No.	Activation Function to		3 LAYER NETWORK (5-7-1)				4-LAYER NETWORK (5-4-4-1)				5 LAYER NETWORK (5-2-2-2-1)			
	Hidden layer(s)	Output layer	Training		Prediction		Training		Prediction		Training		Prediction	
			R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r
1	Logistic	Linear	0.000	0.339	0.000	-1.000	0.000	0.096	0.1935	1.000	0.3035	0.630	0.2792	1.000
2	Logistic	Logistic	0.000	0.691	0.000	1.000	0.0900	0.521	0.1976	1.000	0.000	0.254	0.0792	1.000
3	Linear	Linear	0.000	0.646	0.000	1.000	0.000	0.266	0.000	1.000	0.0223	0.301	0.000	1.000
4	Gaussian	Linear	0.000	0.448	0.000	1.000	0.8829	0.957	0.000	1.000	0.0198	0.583	0.2850	1.000
5	Gaussian	Logistic	0.000	0.605	0.000	1.000	0.000	0.703	0.000	1.000	0.000	0.405	0.000	1.000
6	Tanh	Linear	0.000	0.733	0.000	1.000	0.000	-0.023	0.000	1.000	0.9123	0.955	0.000	-1.000
7	Tanh	Logistic	0.000	0.732	0.000	1.000	0.000	0.024	0.000	1.000	0.000	0.136	0.000	1.000
8	Sine	Linear	0.000	0.733	0.000	1.000	0.000	0.073	0.000	1.000	0.000	0.387	0.000	1.000
9	Sine	Logistic	0.4994	0.742	0.000	1.000	0.000	0.074	0.000	1.000	0.5522	0.822	0.3005	1.000
10	Tanh15	Linear	0.000	0.726	0.000	1.000	0.000	0.030	0.000	1.000	0.8243	0.921	0.000	1.000
11	Tan15h	Logistic	0.4854	0.769	0.000	1.000	0.000	0.031	0.000	1.000	0.000	0.161	0.000	1.000
12	Sym. Log.	Linear	0.000	0.733	0.0442	1.000	0.000	0.046	0.000	1.000	0.3405	0.584	0.000	1.000
13	Sym. Log.	Logistic	0.4720	0.778	0.000	1.000	0.000	0.048	0.000	1.000	0.000	0.108	0.000	1.000
14	Gau. Com.	Linear	0.9463	0.973	0.1393	1.000	0.000	0.690	0.2166	1.000	0.000	0.698	0.000	1.000
15	Gau. com.	Logistic	0.1585	0.684	0.1645	1.000	0.000	0.785	0.4134	1.000	0.000	0.437	0.000	1.000

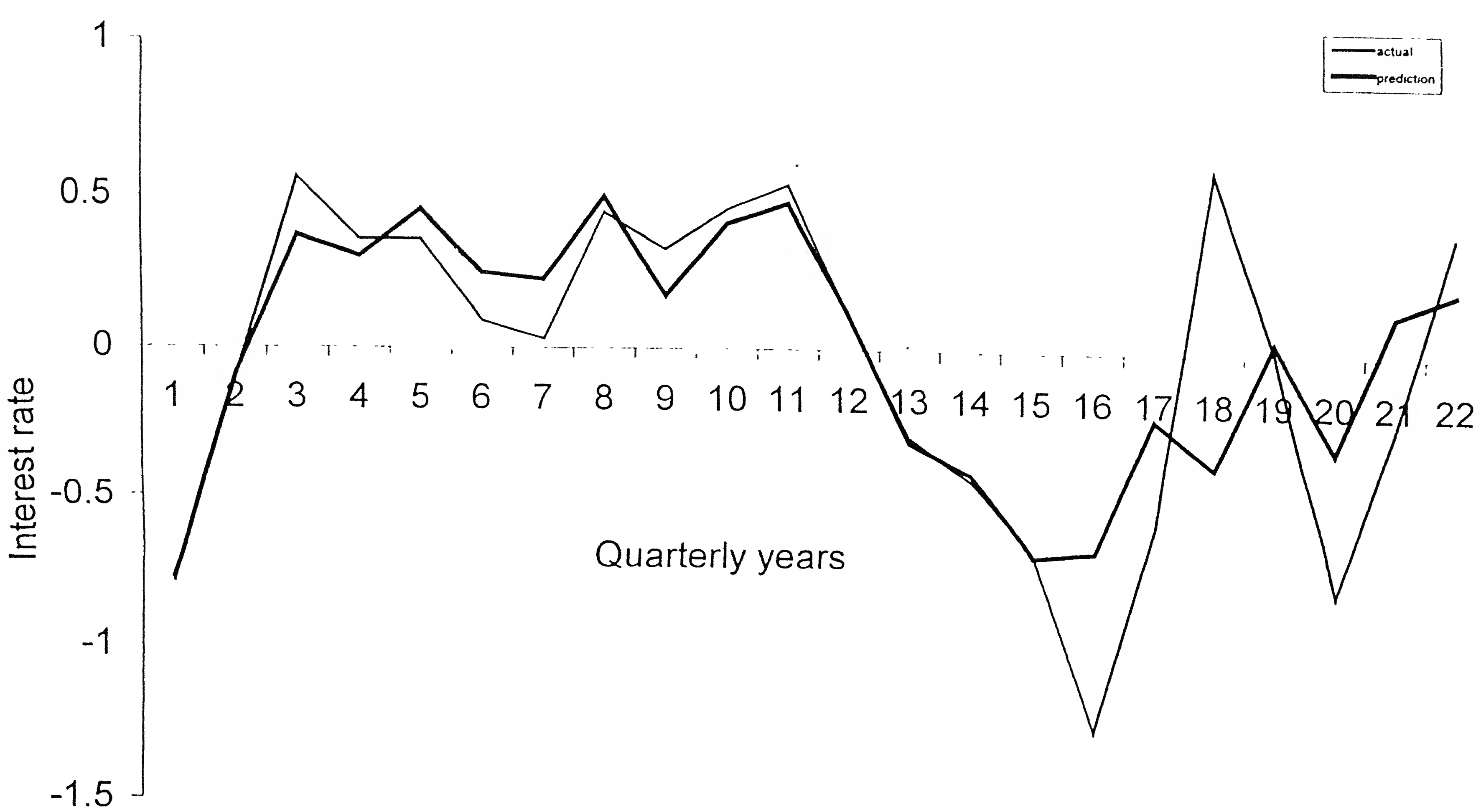


Fig. 3.5: Best Prediction of Interest Rate on 3-layer Jump Connection ANN.

With case No. 14.

In 5-layer network better prediction is found in case no.9, where training is also reasonably good.

It is observed that among all Jump networks, the 3-layer network predicts the interest rate with better accuracy as in case no.14, with threshold 'Gauss comp.' in the hidden layer and 'linear' in the output layer as shown in Fig 3.5.

3.2. Recurrent Neural Networks.

Recurrent neural network is most important ANN for time series problem such as electric load forecasting, financial forecasting. There are three types of recurrent neural network as illustrated below

(a). With feedback from input layer to input layer as shown in Fig 3.6.

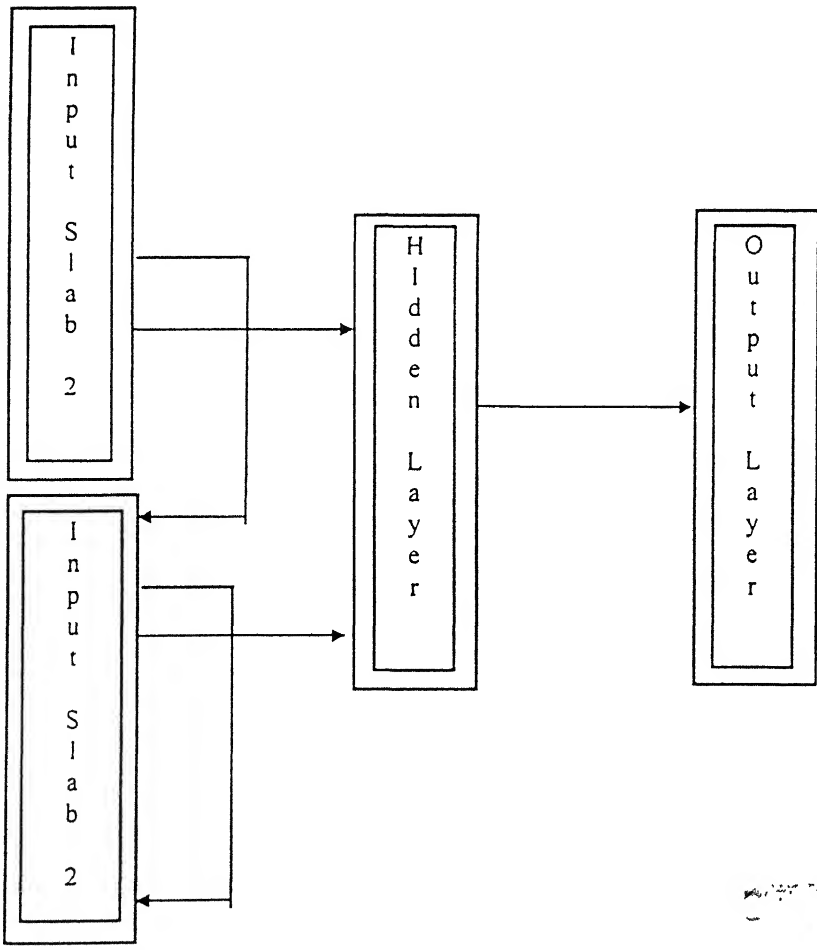


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Fig. 3.6

Fig.3.6: Block diagram of Recurrent Neural Network with feedback from Input layer to Input layer.

(b). With feedback from hidden layer to input layer as shown in fig. 3.7.

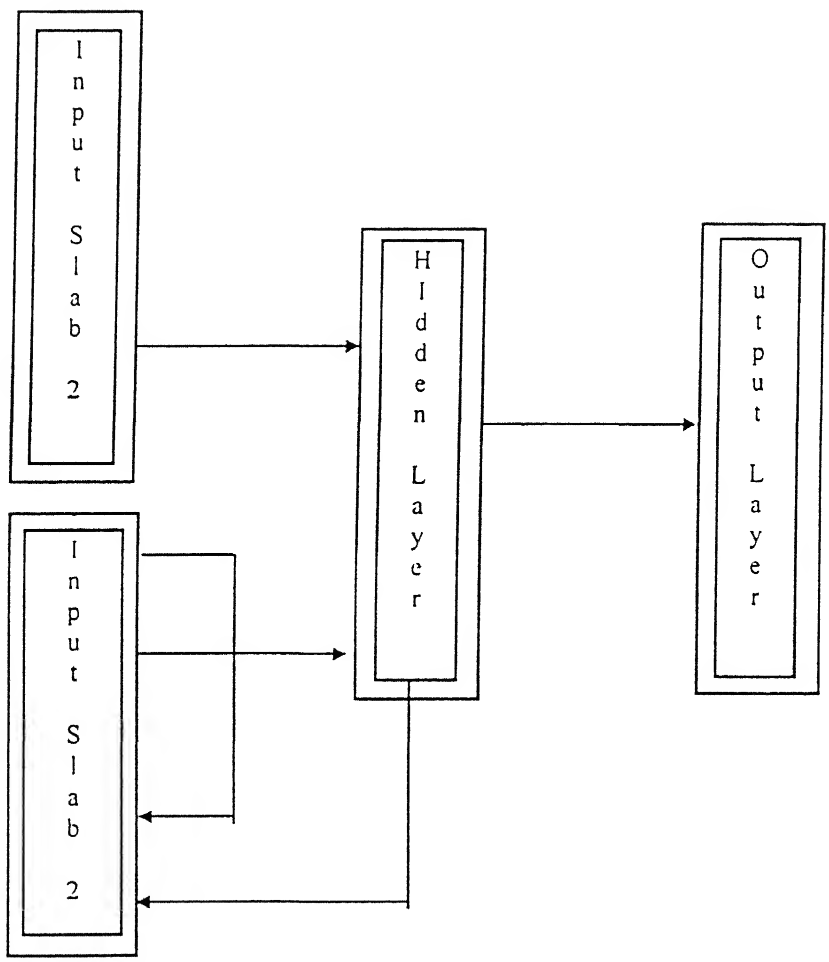


Fig3.7: Block diagram of Recurrent Neural Network with feedback from Hidden layer to Input layer.

(c). **With feedback from output layer to input layer as shown in Fig. 3.8.**

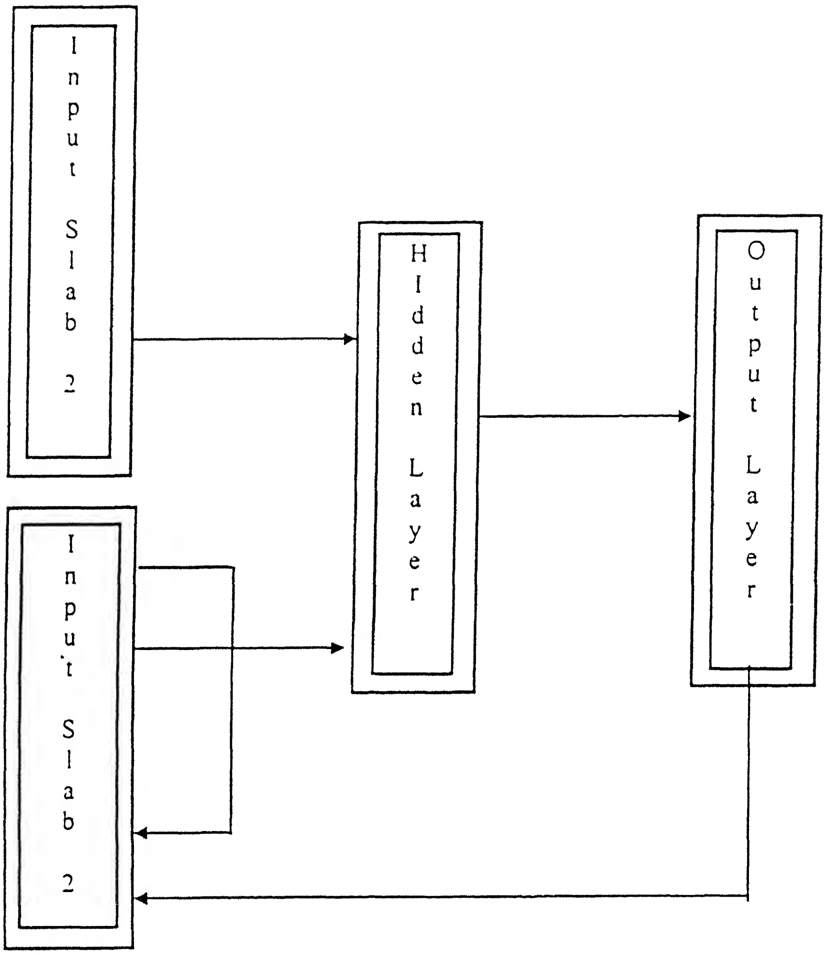


Fig.3.8: Block diagram of Recurrent Neural Network with feedback from Output layer to Input layer.

3.2.1. Short Term Power Demand Prediction.

3.2.1.1. Results

The results of recurrent neural networks are presented in Table (5). For first network as shown in figure 3.6, the best training is found in case No.11, and best prediction is found in case No.2. For 2nd neural network as shown in Fig 3.7, the best training is in

TABLE (5) : SUMMARY OF RECURRENT NEURAL NETWORK (6-18-1).RESULTS FOR STLF

Case No.	Activation Function to		With Feedback from Input layer to Input layer				With Feedback from Hidden layer to Input layer				With Feedback from Output layer to Input layer			
	Hidden layer(s)	Output layer	Training		Prediction		Training		Prediction		Training		Prediction	
			R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r
1	Logistic	Linear	0.8511	0.932	0.7594	0.872	0.8182	0.906	0.7734	0.884	0.7454	0.919	0.6811	0.826
2	Logistic	Logistic	0.8179	0.905	0.7685	0.878	0.8398	0.919	0.7790	0.884	0.8099	0.900	0.7607	0.873
3	Linear	Linear	0.7817	0.913	0.7071	0.870	0.8778	0.937	0.6141	0.786	0.8238	0.911	0.7176	0.851
4	Gaussian	Linear	0.8247	0.915	0.7414	0.865	0.8293	0.913	0.7868	0.896	0.7885	0.897	0.7474	0.875
5	Gaussian	Logistic	0.8106	0.905	0.717	0.848	0.8469	0.921	0.7424	0.878	0.8538	0.926	0.7726	0.880
6	Tanh	Linear	0.9101	0.955	0.7339	0.862	0.9294	0.964	0.5260	0.754	0.8887	0.943	0.6857	0.839
7	Tanh	Logistic	0.8856	0.945	0.7226	0.860	0.9309	0.965	0.7371	0.866	0.8964	0.947	0.7343	0.860
8	Sine	Linear	0.8573	0.926	0.7413	0.861	0.909	0.954	0.5145	0.725	0.8565	0.926	0.6774	0.842
9	Sine	Logistic	0.8473	0.923	0.7363	0.860	0.8863	0.941	0.7700	0.883	0.8510	0.927	0.7706	0.881
10	Tanh15	Linear	0.906	0.954	0.7389	0.875	0.8874	0.944	0.5430	0.794	0.8786	0.938	0.7074	0.851
11	Tan15h	Logistic	0.9192	0.959	0.7029	0.860	0.9088	0.953	0.6528	0.815	0.8833	0.940	0.7461	0.865
12	Sym. Log.	Linear	0.8471	0.921	0.7527	0.868	0.839	0.918	0.7741	0.882	0.7885	0.930	0.6514	0.808
13	Sym. Log.	Logistic	0.7673	0.893	0.7074	0.855	0.8512	0.928	0.7141	0.858	0.8534	0.925	0.7705	0.881
14	Gau. Com.	Linear	0.8431	0.919	0.7583	0.874	0.8108	0.914	0.7390	0.864	0.7334	0.887	0.6298	0.796
15	Gau. com.	Logistic	0.8639	0.930	0.7548	0.870	0.7686	0.989	0.6913	0.835	0.8336	0.924	0.7491	0.868

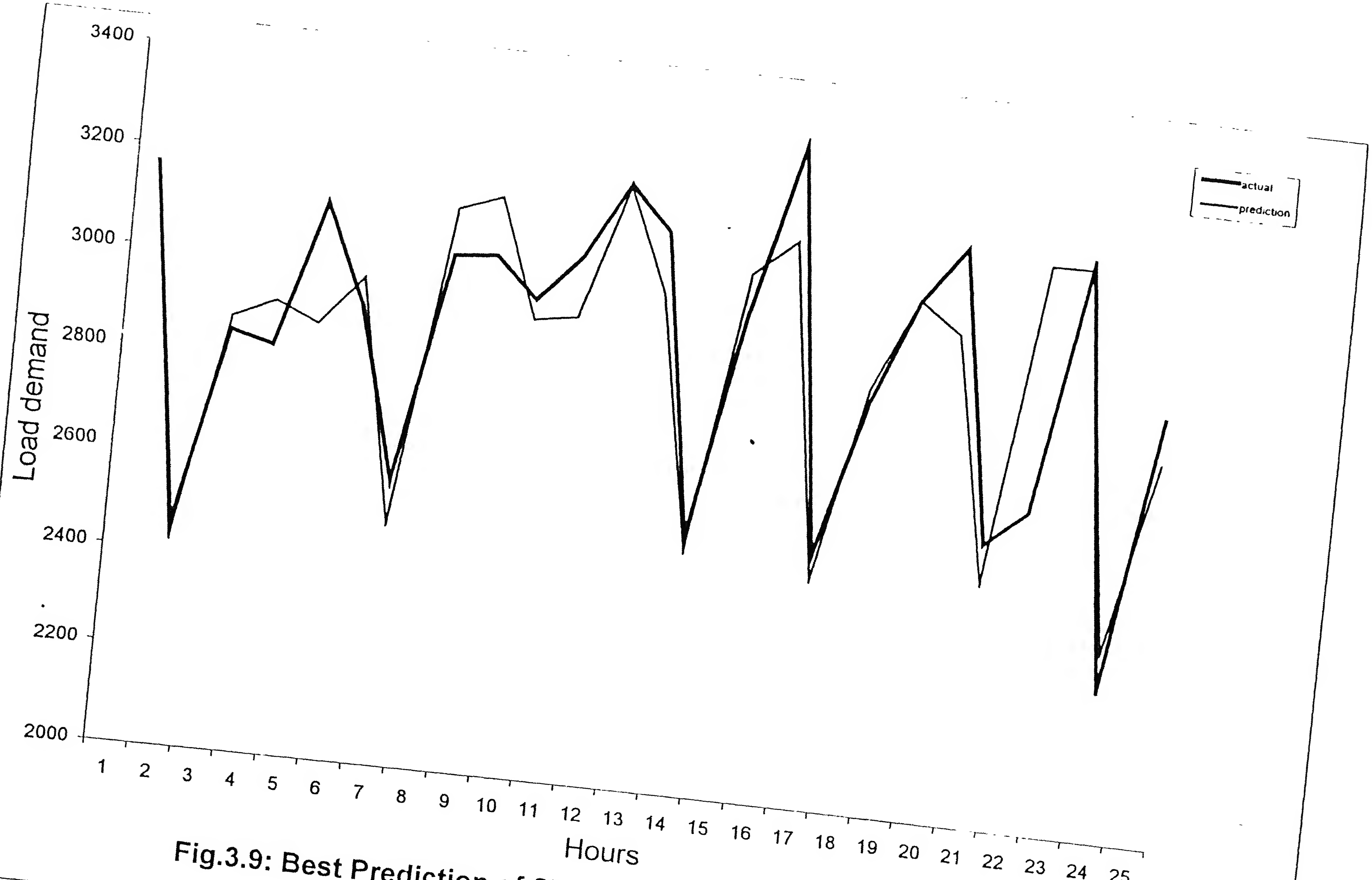


Fig.3.9: Best Prediction of STLF on Recurrent Neural Network. With case No. 4.

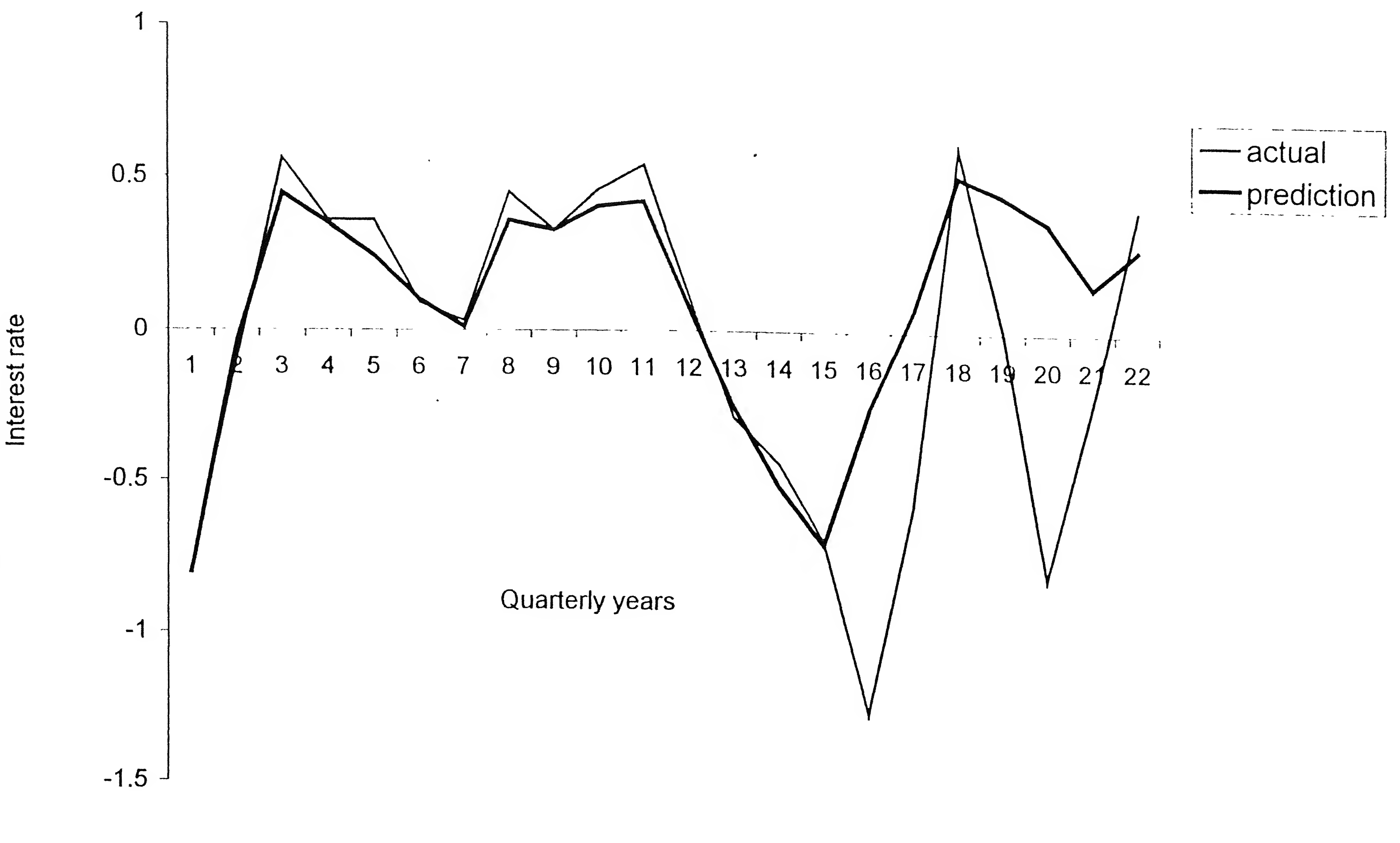


Fig. 3.10: Best Prediction of Interest Rate on Recurrent Neural Net With case No. 1.

case 7., and best prediction is in caseNo.4.for 3rd network as shown in figure 3.8, the training is in case 7., and best prediction is in caseNo.5.

Concluding from all the above recurrent neural network the best model is as shown in figure 3.7 with threshold function 'tanh' to hidden layer and 'logistic' in output layer which gives best power demand prediction in recurrent network as shown in Fig 3.9.

3.2.2. Interest Rate Prediction.

3.2.2.1. Results

Interest rate prediction using recurrent neural networks is presented in Table (6). In first neural network (fig.3.6) the best prediction is with case No.1. In 2nd neural network (fig. 3.7) the best prediction is with case No.2. and in 3rd neural network (fig. 3.8) the best prediction is with case No.11.

From all above recurrent neural network the best model for prediction of Interest rate is in case No 1 with threshold function 'logistic' to hidden layer and 'linear' to the output layer, result are shown in Fig 3.10.

3.3. Ward Neural Networks.

There are three types of Ward neural network are used as follow:

TABLE (6) : SUMMARY OF RECURRENT NEURAL NETWORK (5-7-1) RESULTS FOR FINANCIAL FORECASTING

Case No.	Activation Function to		With Feedback from Input layer to Input layer				With Feedback from Hidden layer to Input layer				With Feedback from Output layer to Input layer			
	Hidden layer(s)	Output layer	Training		Prediction		Training		Prediction		Training		Prediction	
			R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r
1	Logistic	Linear	0.9766	0.993	0.9998	1.000	0.4662	0.848	0.000	1.000	0.9906	0.995	0.000	1.000
2	Logistic	Logistic	0.8717	0.934	0.6630	1.000	0.8921	0.945	0.4289	1.000	0.9827	0.992	0.000	1.000
3	Linear	Linear	0.000	0.625	0.000	1.000	0.000	-0.352	0.000	1.000	0.000	0.699	0.000	1.000
4	Gaussian	Linear	0.000	0.643	0.000	1.000	0.4913	0.805	0.000	1.000	0.9887	0.994	0.1560	1.000
5	Gaussian	Logistic	0.8236	0.945	0.3558	1.000	0.7897	0.952	0.000	1.000	0.7972	0.913	0.000	1.000
6	Tanh	Linear	0.000	0.666	0.000	1.000	0.000	0.697	0.000	1.000	0.8478	0.929	0.0689	1.000
7	Tanh	Logistic	0.000	0.653	0.000	1.000	0.9154	0.957	0.000	1.000	0.6301	0.805	0.2973	1.000
8	Sine	Linear	0.000	0.669	0.000	1.000	0.000	0.000	0.000	1.000	0.9957	0.998	0.000	-1.000
9	Sine	Logistic	0.000	0.654	0.000	1.000	0.7304	0.883	0.000	1.000	0.5565	0.793	0.000	1.000
10	Tanh15	Linear	0.000	0.655	0.000	1.000	0.000	0.677	0.000	1.000	0.9770	0.992	0.000	1.000
11	Tan15h	Logistic	0.0018	0.648	0.000	1.000	0.3007	0.768	0.000	1.000	0.7068	0.862	0.6132	1.000
12	Sym. Log.	Linear	0.000	0.665	0.000	1.000	0.5942	0.783	0.000	1.000	0.0625	0.668	0.000	1.000
13	Sym. Log.	Logistic	0.000	0.655	0.000	1.000	0.8350	0.927	0.000	1.000	0.7022	0.933	0.000	0.000
14	Gau. Com.	Linear	0.8794	0.941	0.9626	1.000	0.9899	0.997	0.000	-1.000	0.9294	0.965	0.000	1.000
15	Gau. com.	Logistic	0.8394	0.924	0.8612	1.000	0.8803	0.946	0.000	-1.000	0.8342	0.915	0.000	1.000

(a). With 2 slabs in the hidden layer as shown in Fig 3.11.

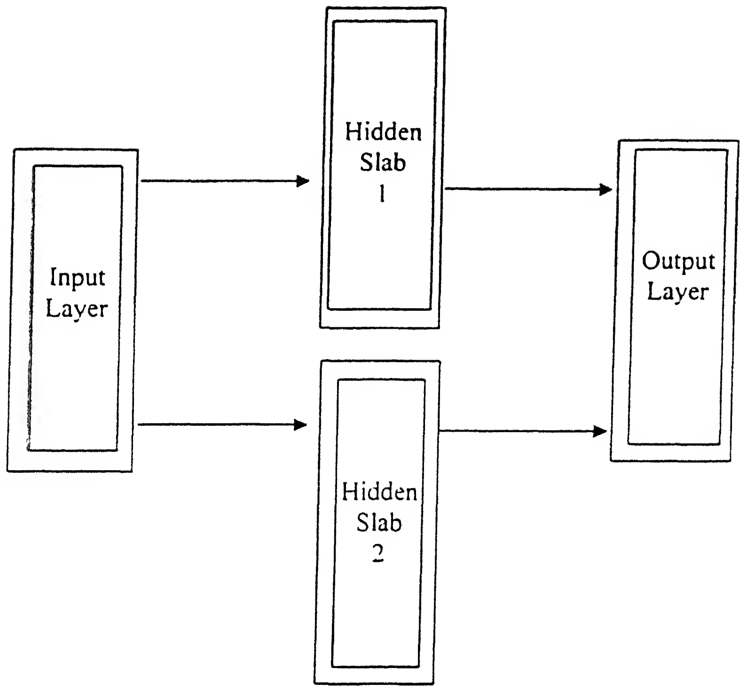


Fig.3.11: Ward Neural Network with two slabs in hidden layer.

(b). With 3 slabs in the hidden layer as shown in Fig 3.12.

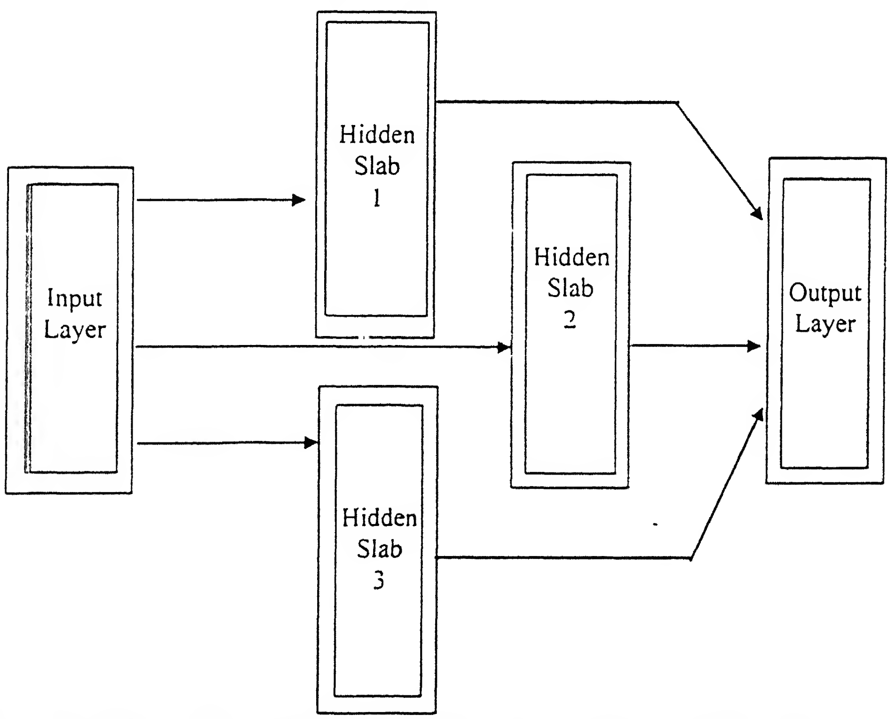


Fig.3.12: Ward Neural Network with three slabs in hidden layer.

(c). With 2 slabs in the hidden layer and a jump connection between the input and output layers as shown in Fig 3.13.

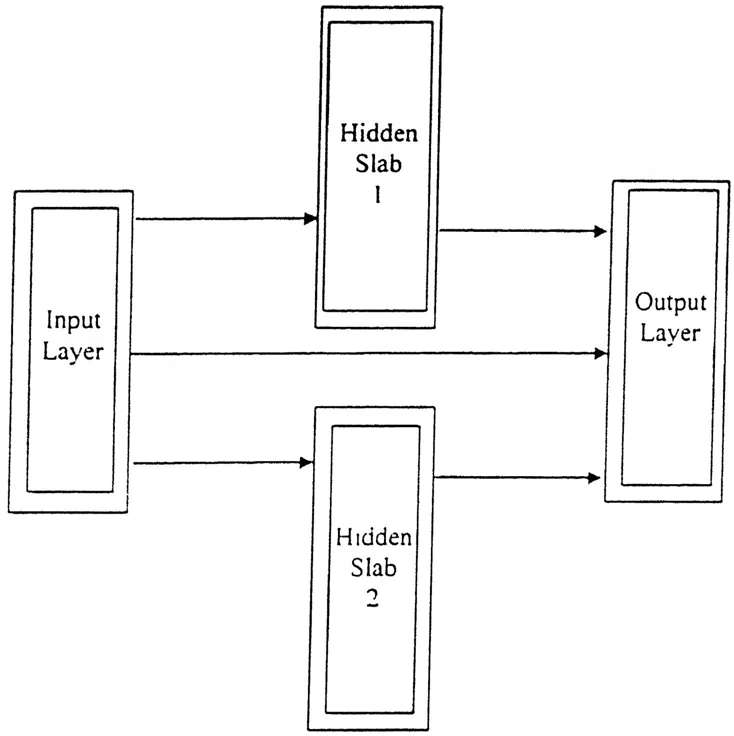


Fig.3.13: Ward Neural Network with two slabs in hidden layer and Jump. connection

3.3.1. Short Term Power Demand Prediction.

3.3.1.1. Results

The results of power demand prediction are illustrated in Table (7), whereas, In first network (fig.3.11) the best training result is with case No 13. And the best prediction with case No.8. For 2nd network (Fig.3.12) the best training and best prediction are with cases 6 and 8 respectively. For 3rd network (Fig.3.13) the best training and prediction are with cases 7 and 4 respectively

From all above Ward neural network the best model for prediction of power demand is in case 7. with threshold function 'tanh' to hidden layer and 'logistic' to the output layer, as the best prediction is shown in Fig 3.14.

TABLE (7) : SUMMARY OF WARD NEURAL NETWORK (6-18-1) RESULTS FOR STLF

Case No.	Activation Function to		With 2-Slabs in Hidden layer (6-9,9-1)				With 3-Slabs in Hidden layer (6-6,6,6-1)				With 2-Slabs in Hidden layer with Jump connection			
	Hidden layer(s)	Output layer	Training		Prediction		Training		Prediction		Training		Prediction	
			R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r
1	Logistic	Linear	0.8635	0.929	0.7808	0.884	0.8655	0.930	0.7703	0.878	0.8610	0.929	0.7754	0.881
2	Logistic	Logistic	0.8608	0.929	0.7767	0.883	0.8619	0.929	0.7779	0.883	0.8564	0.926	0.7785	0.883
3	Linear	Linear	0.8641	0.931	0.7700	0.879	0.8608	0.928	0.7643	0.875	0.8444	0.922	0.7734	0.862
4	Gaussian	Linear	0.8855	0.941	0.7821	0.886	0.8580	0.927	0.7730	0.880	0.8887	0.943	0.8052	0.900
5	Gaussian	Logistic	0.8550	0.926	0.7714	0.879	0.8244	0.908	0.7595	0.873	0.8782	0.937	0.7778	0.882
6	Tanh	Linear	0.8914	0.944	0.7697	0.878	0.9167	0.957	0.7782	0.886	0.8756	0.936	0.7742	0.882
7	Tanh	Logistic	0.8717	0.936	0.7760	0.881	0.9100	0.954	0.7893	0.890	0.9284	0.964	0.7741	0.882
8	Sine	Linear	0.8729	0.935	0.7968	0.895	0.8833	0.940	0.8016	0.897	0.8788	0.938	0.7674	0.877
9	Sine	Logistic	0.8937	0.945	0.7439	0.863	0.8863	0.944	0.6979	0.847	0.9007	0.949	0.7526	0.870
10	Tanh15	Linear	0.8626	0.931	0.7783	0.883	0.8927	0.945	0.7656	0.879	0.8827	0.940	0.7693	0.878
11	Tan15h	Logistic	0.8817	0.945	0.7498	0.872	0.8973	0.947	0.7945	0.891	0.8836	0.940	0.7822	0.885
12	Sym. Log.	Linear	0.8826	0.939	0.7756	0.881	0.8728	0.935	0.7826	0.885	0.8732	0.935	0.7772	0.882
13	Sym. Log.	Logistic	0.9068	0.952	0.7000	0.841	0.9117	0.955	0.7041	0.852	0.8940	0.947	0.7888	0.890
14	Gau. Com.	Linear	0.8855	0.941	0.7821	0.886	0.8682	0.933	0.7878	0.889	0.8887	0.943	0.8052	0.900
15	Gau. com.	Logistic	0.8550	0.926	0.7714	0.879	0.8972	0.947	0.7871	0.889	0.8782	0.937	0.7778	0.882

3.3.2. Interest Rate Prediction.

3.3.2.1. Results

The Interest rate prediction on Ward neural networks are illustrated in Table (8), where in for 1st network (Fig.3.11) the best training and prediction are found with case No 4., for 2nd network (Fig.3.12) the best training and prediction are with cases 14 and 5 respectively, and for 3rd network (Fig.3.13) the best training and prediction are with cases 11 and 1 respectively.

From all above Ward neural network the best model selecting for interest rate prediction is in case No. 4 with threshold function 'Gaussian' to hidden layer and 'linear' to the output layer.

3.4. Conclusion.

The results obtained for prediction of power demand and interest rate through all architecture of non conventional neural network have been compared, and found the Recurrent neural network gives the best results for both the problem. For the short-term power demand prediction the neural network with feedback from the hidden layer to the input layer with threshold function 'tanh' to hidden layer and 'logistic' to the output layer gives better prediction. Whereas for the Interest rate prediction the neural network with feedback from the Input layer to the input layer with threshold function 'logistic' to hidden layer and 'linear' to the output layer gives better prediction.

Recurrent neural networks have been successfully used in predicting both problem as stated above, because recurrent networks can learn sequences, this

TABLE (8) : SUMMARY OF WARD NEURAL NETWORK RESULTS FOR FINANCIAL FORECASTING

ase No.	Activation Function to		With 2-Slabs in Hidden layer (5-4,4-1).				With 3-Slabs in Hidden layer. (5-2,2,2-1).				With 2-Slabs in Hidden layer wit Jump connection.			
	Hidden layer(s)	Output layer	Training		Prediction		Training		Prediction		Training		Prediction	
			R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r	R-Squared	r
1	Logistic	Linear	0.000	-0.065	0.000	-1.000	0.8206	0.915	0.000	-1.000	0.2244	0.576	0.1741	1.00
2	Logistic	Logistic	0.1646	0.558,	0.0582	1.000	0.000	0.583	0.000	1.000	0.000	0.196	0.000	-1.00
3	Linear	Linear	0.3330	0.600,	0.2593	1.000	0.3046	0.773	0.0427	1.000	0.000	0.765	0.000	1.00
4	Gaussian	Linear	0.8245	0.924	0.1860	1.000	0.000	0.596	0.000	-1.000	0.000	-0.292	0.000	-1.00
5	Gaussian	Logistic	0.0330	0.829	0.289	1.000	0.4323	0.733	0.2836	1.000	0.000	0.342	0.000	-1.00
6	Tanh	Linear	0.0900	0.800	0.000	1.000	0.0272	0.675	0.000	1.000	0.1295	0.761	0.000	1.00
7	Tanh	Logistic	0.000	0.640	0.2189	1.000	0.0672	0.795	0.2800	1.000	0.5496	0.762	0.000	1.00
8	Sine	Linear	0.5239	0.843	0.000	1.000	0.000	0.759	0.000	1.000	0.9875	0.994	0.000	1.00
9	Sine	Logistic	0.000	0.633	0.2207	1.000	0.000	0.704	0.1464	1.000	0.3191	0.672	0.000	1.00
10	Tanh15	Linear	0.000	0.783	0.000	1.000	0.000	0.658	0.000	1.000	1.000	1.000	0.000	1.000
11	Tan15h	Logistic	0.000	0.695	0.3523	1.000	0.000	0.586	0.000	1.000	0.9978	0.999	0.000	-1.00
12	Sym. Log.	Linear	0.8353	0.926	0.000	1.000	0.000	0.725	0.000	1.000	0.8078	0.901	0.000	-1.00
13	Sym. Log.	Logistic	0.000	0.549	0.0962	1.000	0.000	0.651	0.000	1.000	0.7750	0.885	0.000	-1.00
14	Gau. Com.	Linear	0.8245	0.924	0.1860	1.000	0.9809	0.991	0.000	1.000	0.000	-0.292	0.000	1.000
15	Gau. com.	Logistic	0.0330	0.829	0.2890	1.000	0.000	0.672	0.000	1.000	0.000	0.342	0.000	-1.000

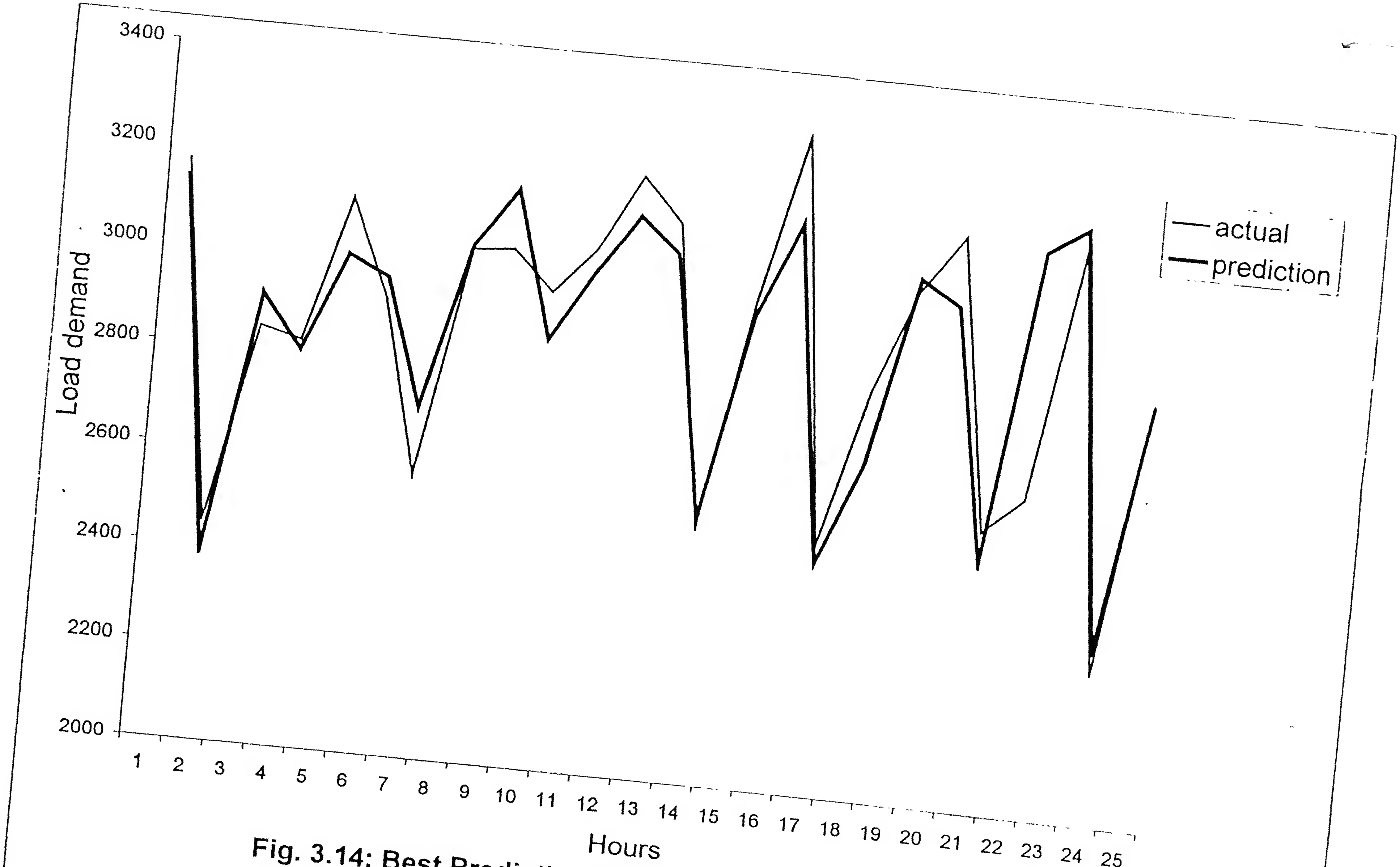


Fig. 3.14: Best Prediction of STLF on Ward Network With case No. 7.

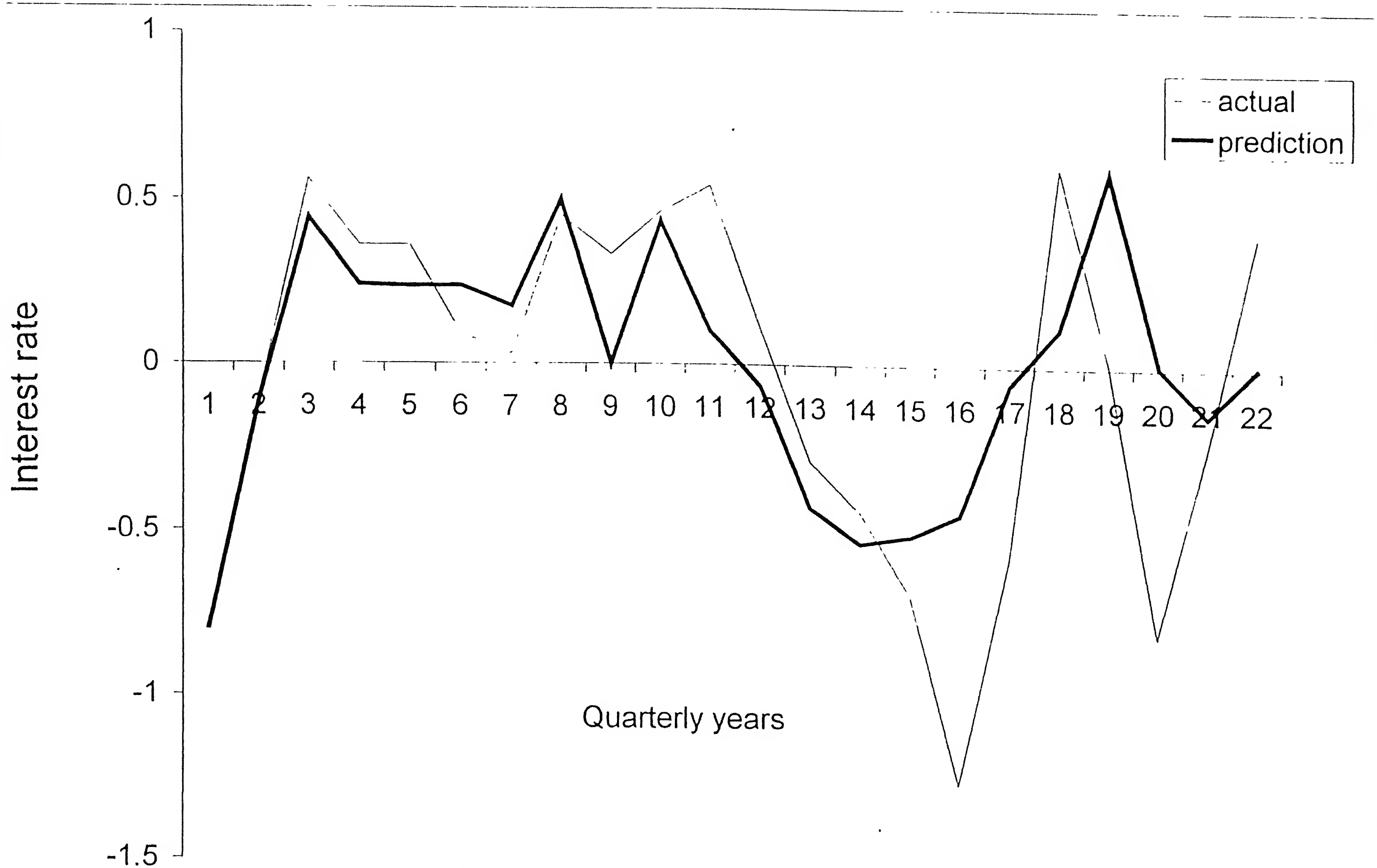
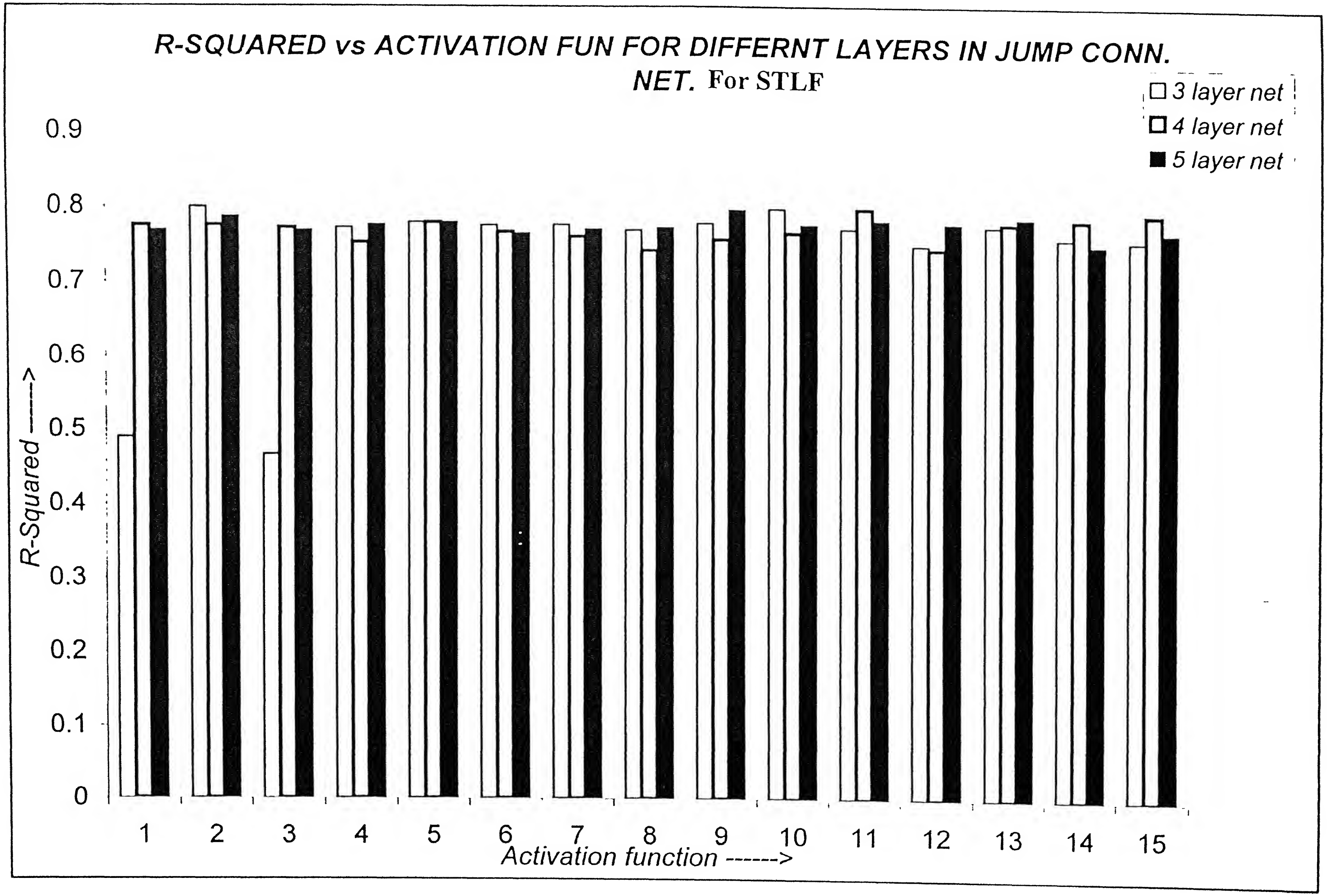


Fig.3.15: Best Prediction of Interest Rate on Ward Network. With case No. 4.

network are excellent for time series data. They have the slight disadvantage of taking longer to train.

Recurrent network is the feedback neural network, this group of networks performs recall computation with feedback operational. These networks can be considered as dynamical systems and a certain time interval is needed for their recall to be completed. Feedback networks are also called recurrent networks. Whereas non-feedback network popularly known as feedforward system in neural network, has an one way data flow from input towards output. In non- feedback system the output does not depends upon the past history of the inputs.

As stated above paragraph the feedback concept brought to neural network to improve reliability and operational performance as seen in the results of the recurrent neural network, which gives the best prediction compared to the non-feedback neural network.


R-SQUARED vs ACTIVATION FUN FOR DIFFERNT LAYERS IN JUMP CONN. NET. For STLF
3 layer net
4 layer net
5 layer net
R-Squared ------>
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
Activation function ------>

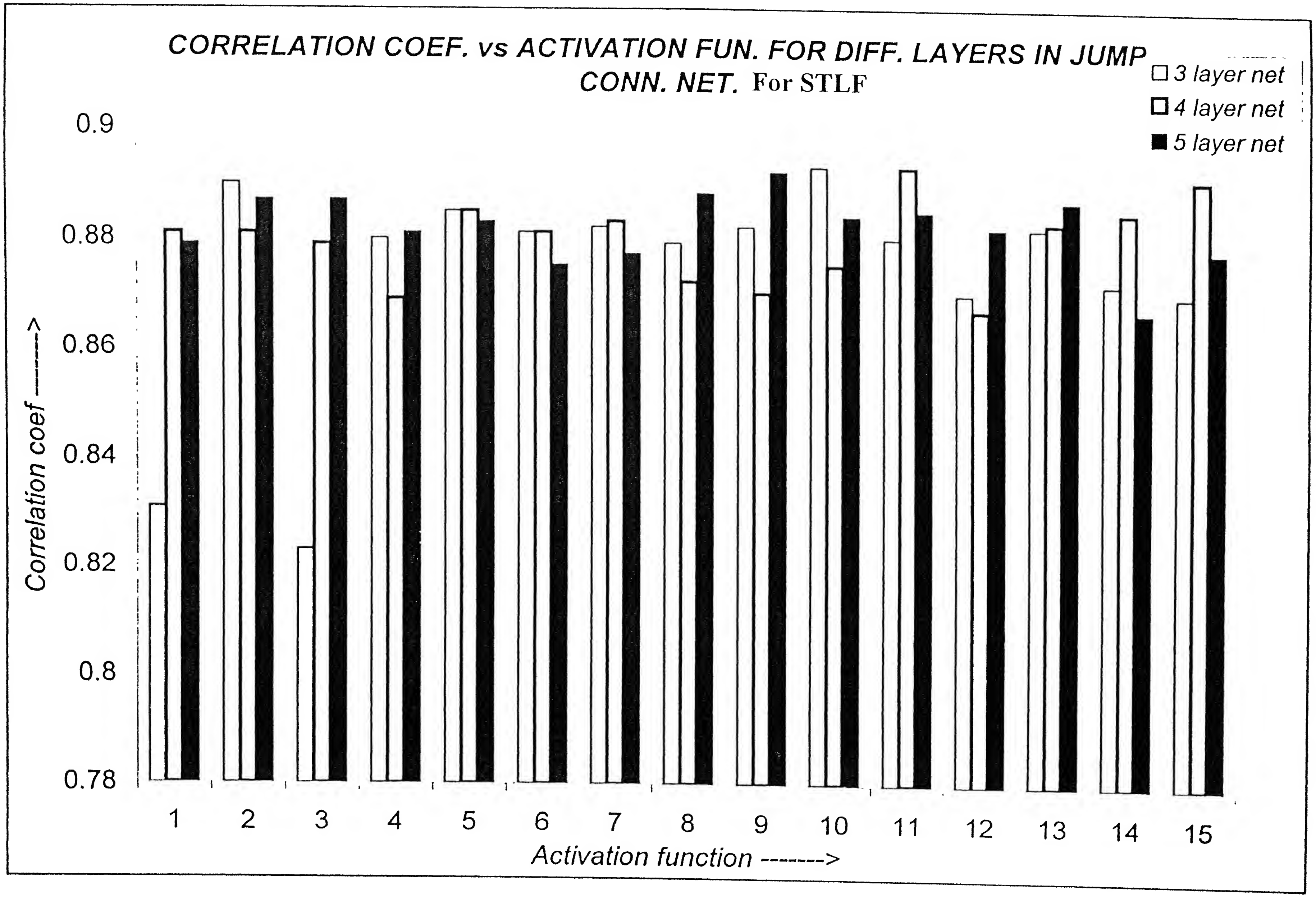
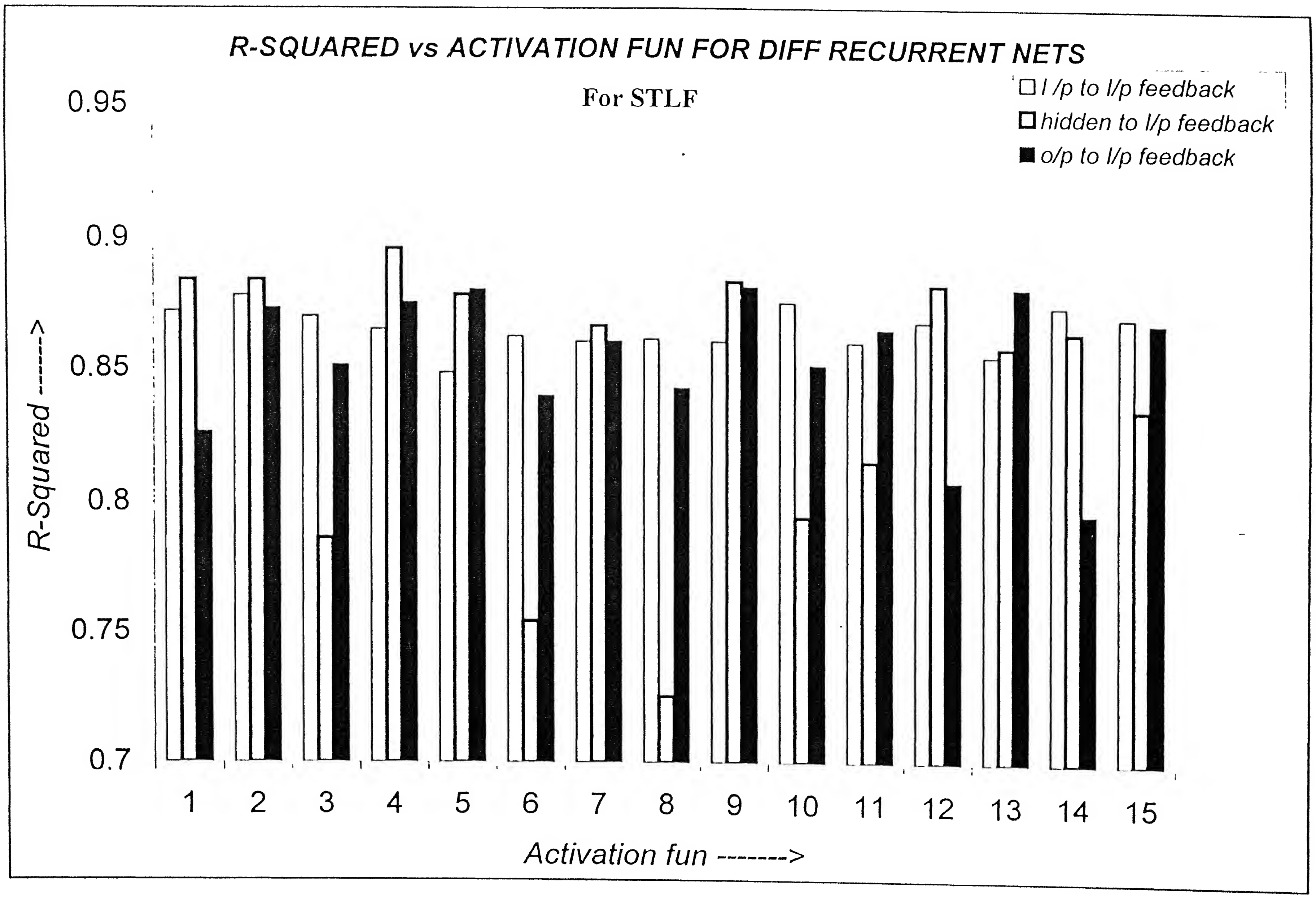
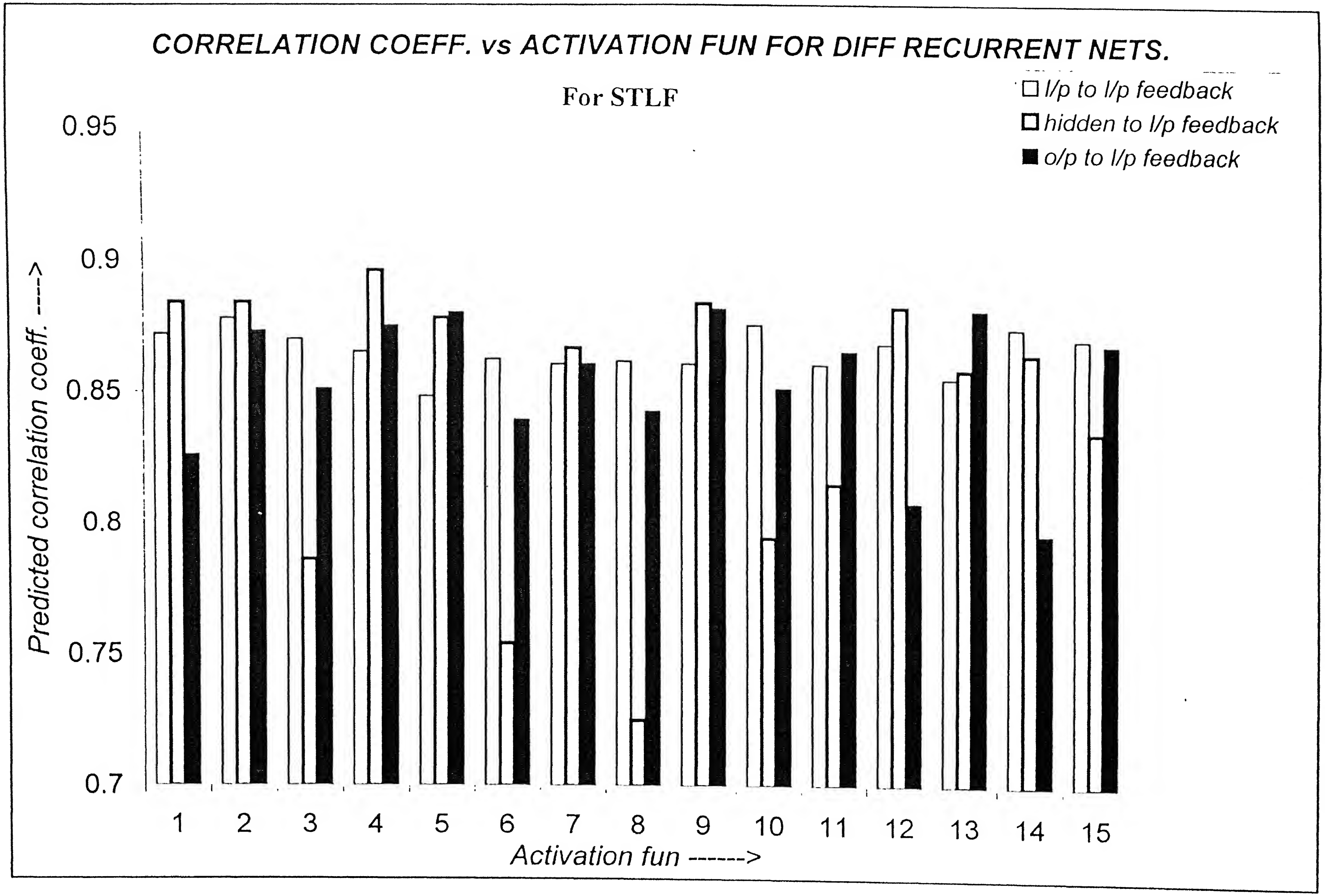

CORRELATION COEF. vs ACTIVATION FUN. FOR DIFF. LAYERS IN JUMP CONN. NET. For STLF
3 layer net
4 layer net
5 layer net
0.9
0.88
0.86
0.84
0.82
0.8
0.78
Correlation coef -------->
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
Activation function ------->

Fig. 3.17


R-SQUARED vs ACTIVATION FUN FOR DIFF RECURRENT NETS
For STLF
I /p to I/p feedback
hidden to I/p feedback
o/p to I/p feedback
0.95
0.9
0.85
0.8
0.75
0.7
R-Squared ------>
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
Activation fun ------>



CORRELATION COEFF. vs ACTIVATION FUN FOR DIFF RECURRENT NETS.
For STLF
I/p to I/p feedback
hidden to I/p feedback
o/p to I/p feedback
0.95
0.9
0.85
0.8
0.75
0.7
Predicted correlation coeff. ---->
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
Activation fun ------>

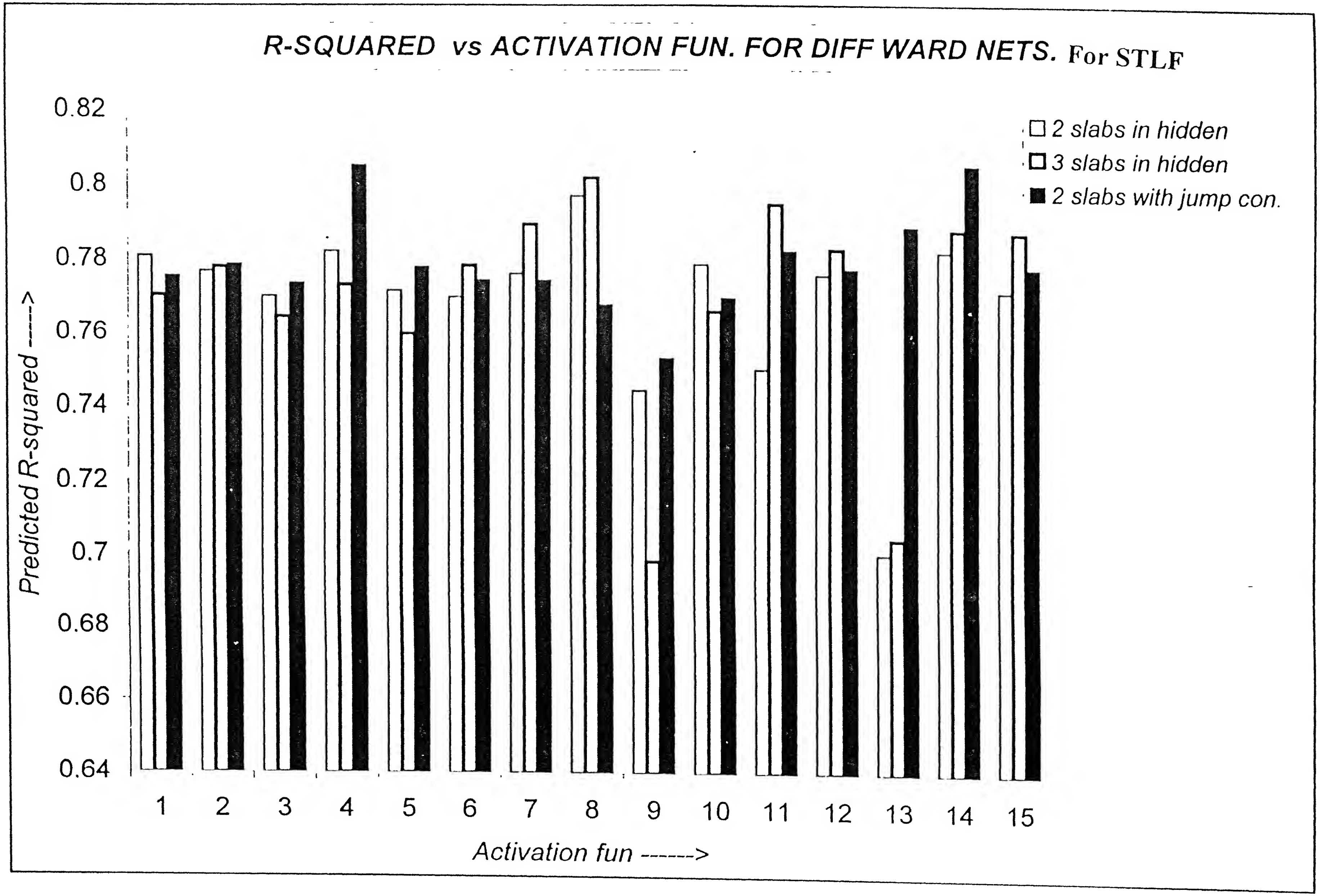

R-SQUARED vs ACTIVATION FUN. FOR DIFF WARD NETS. For STLF
2 slabs in hidden
3 slabs in hidden
2 slabs with jump con.
Predicted R-squared ----->
0.82
0.8
0.78
0.76
0.74
0.72
0.7
0.68
0.66
0.64
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Activation fun ------>

Fig. 3.20

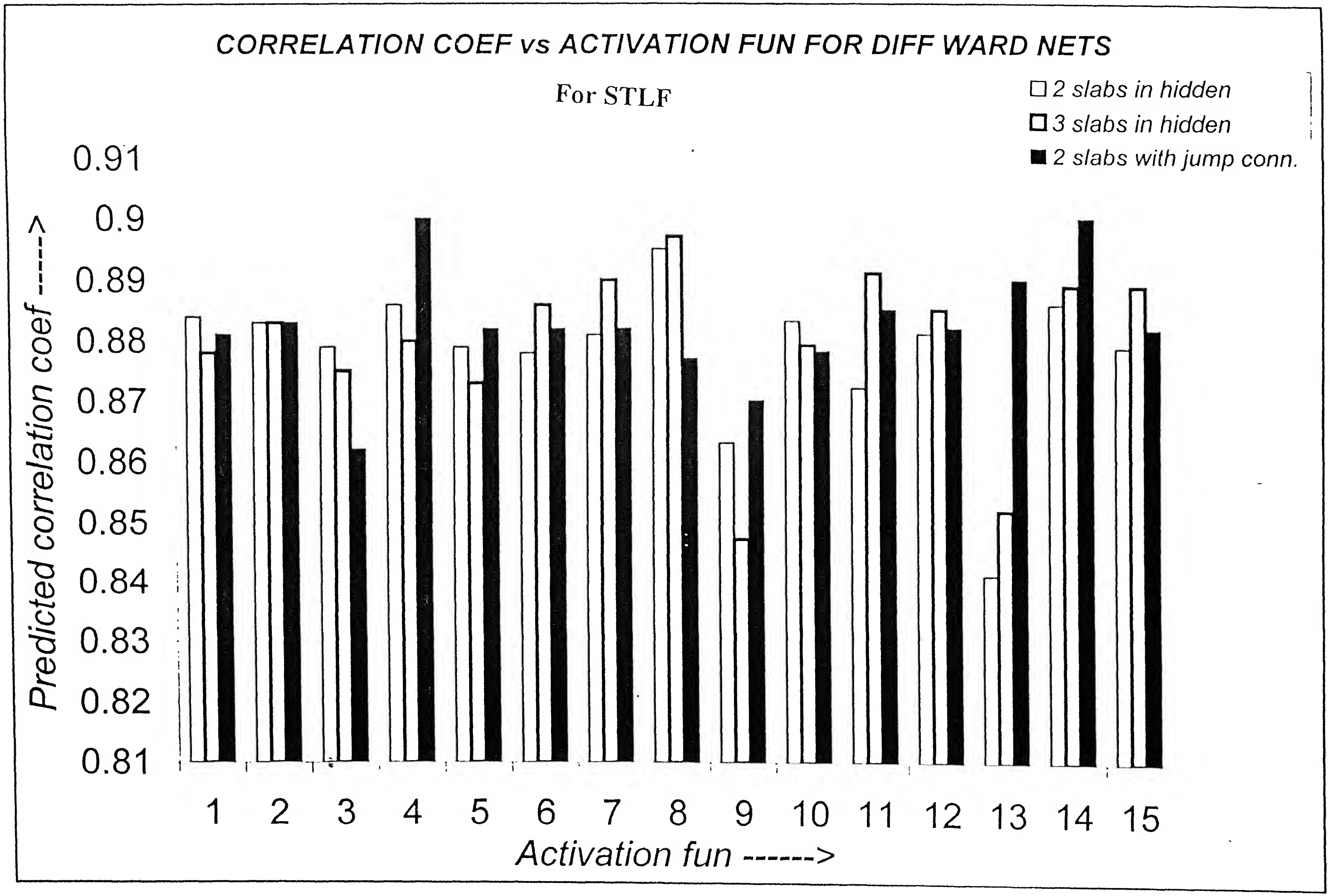

CORRELATION COEF vs ACTIVATION FUN FOR DIFF WARD NETS
For STLF
2 slabs in hidden
3 slabs in hidden
2 slabs with jump conn.
Predicted correlation coef ----->
0.91
0.9
0.89
0.88
0.87
0.86
0.85
0.84
0.83
0.82
0.81
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Activation fun ------>

Fig. 3.21

Chapter 4.

CONCLUSION AND FUTURE WORK SCOPE.

4.1. Conclusion

The short term load forecasting and financial forecasting, using Artificial Neural Networks (ANNs), are investigated in this thesis and the results are analysed. The Short-Term Load Forecast (STLF) plays an important role in the secure operation of a power system.. Accurate load forecast provides the system dispatchers with timely information to operate the system economically and reliably. The application of neural networks for financial forecasting and modelling has been very popular.

The overall conclusion for both power demand prediction and interest rate prediction is selecting best model of ANN. For short-term power demand prediction the best model is suggesting 4-layer standard backpropagation neural network with activation function 'tanh' to the hidden layers and 'logistic' to the output layer. For interest rate prediction the best model is suggesting recurrent neural network with

feedback from input layer to input layer. with activation function 'logistic' to the hidden layers and 'linear' to the output layer.

4.2. Future Work

(1) The influence of various aggregation functions on the quality of prediction.

(2) Influence of various optimizations along with different aggregation and thresholding function on the quality of prediction.

(3) New Neural Architecture can be used to enhance the speed of Computation so that the on-line training and prediction can go simultaneously.

(4) Use of second order learning imposed on new architecture may provide better accuracy along with fast result.

(5) Hybrid Neural Networks is another possibility together with the new architecture which would improve the result as well as computation time and thereby reducing the cost of operation.

REFERENCES

[1]. Lippman R. P., April 1987, "An Introduction to computing with Neural Network" IEEE ASSO Mag. 4 No. 2, pp 4-22.

[2]. Hush D. R. and Horne B. G., Jan 1993 "Progress in supervised Neural Networks" IEEE ASSP Mag pp.8-39.

[3]. Melsa, P. J. W., Aug. 1989, "Neural Networks: A Conceptual Overview", Report TRC-89-08 Tellab Research Center, Mishawaka, Indiana, U.S.A.

[4]. Dillion, T. S., 1991, "Artificial Neural Network Application to Power System and Their Relationship to Symbolic Methods", Elect. Power Energy Syst., 13, (2), pp 66-72.

[5]. Windrow B and Lehr M. A., Sept. 1990 "30 years of Adaptive Neural Network: Perceptron, Madaline, and Backpropagation" Proc IEEE Vol-78, No. 9 pp 1415-1442.

[6]. Sinha M., Kalra P. K., and Kumar K. "Parameter Estimation Using Compensatory Neural Networks", special issue of SADHANA on system identification and modelling 1999 to be publiced, Indian Academy of Science.

[7]. Stephen T. Welstead "Neural Network and Fuzzy logic Applications in C/C++".

[8]. Simon Haykin, Maxwell Macmillan. "Neural Networks - A Comprehensive Foundation".

[9]. Kalra, P. K. amd et. al., 1993, 'Short Term Electric Load Forecasting Using Artificial Neural Networks' Proc-IV Symp : Expert System Application to Power System, Melbourne Australia, pp 159-165.

[10]. Kalra, P. K., Sept. 1995, "Paradigms of Artificial Neural Networks for Optimasation, Process Modelling and Control".

[11]. Hagan M. T., and Behr S. M., 1987, 'The time series Approach to Short term load forecasting'. IEEE Trans, PWRS-2 pp 785-791.

[12]. Moghram, I. and Rahman, S., 1989", Analysis and Evaluation of Five Short Term Load Forecasting Techniques", IEEE Trans PWRS-4, pp 1484-1491.

[13]. Dillion, T. S., Sestito S. and Leng S., 1991 'Short Term Load Forecasting Using Adaptive Neural Network' Elect. Power Energy System, 13(4) pp 186-192.

[14]. Y. Y. Hsu and C. C. Yang, "Design of artificial network to short term load forecasting, Part I & II", IEEE Proc., Part-C, Vol.. 138, pp 407-418, Sep. 1991.

[15]. D. C. Park, M. A. El-Sharkawi, R.J. Marks et. al., "Electric load forecasting using ANN", IEEE Trans. PWRS, vol. 6, No. 2, pp 442-449, Nov.1991.

[16]. Bacha, Hamid, Walter Meyer, "A Neural Network Architecture for Load Forecasting", Proceedings of the 1992 International Joint Conference on Neural Networks, Vol. 2, pp 442-447, June 1992

[17]. J. T. Conner, L. E. Atlas, D. Martin, "Recurrent Neural Network and Load forecasting", First international Forum on Applications of Neural Networks to Power Systems, pp 22-25, July 1991.

[18]. IEEE Committee Report, "Load forecasting bibliography Phase-I", IEEE Trans. Power Apparatus and Systems, Vol. 99. Pp 53-58, 1980.

[19]. T. S. Chen et. al., "Short- term load forecassting using an artificial neural network" Elect. Energy and Power Systems, Vol. 13, No. 4, pp 185-192, Aug. 1991.

[20]. Rahman S., 1990, "Fomulation and analysis of Rule Based Short Term load Forecasting Algorithm", Proc. IEEE, pp 805-816.

[21]. Park, D. C. etal., 1991, "Electric Load Forecasting Using an Artificial Neural Networks" IEEE Trans Power System 6, pp442-449.

[22]. Gross, G. and Galiana, F. O. , 1987, "Short Term Load forecasting" Proc. IEEE, V-75, pp 1558-1573.

[23]. Suri Vemuri, Wen Liang Huang and Don J. Nelson, "On-line algorithms for forecasting hourly loads of an electric utility," IEEE Trans on Power Appr. & Sys., vol. PAS-100.

APPENDIX

TRAINING FILE FOR SHORT TERM LOAD FORECASTING

3hr	2hr	1hr	3week	2week	1week	output
3161	3110	3092	2966	3177	2871	2929
3110	3092	2929	2895	3043	2790	2847
3092	2929	2847	2965	3135	2947	2986
2929	2847	2986	3094	3161	2975	2946
2847	2986	2946	3073	3188	2893	3068
2986	2946	3068	3041	3210	2825	3095
2946	3068	3095	2936	3244	2887	3119
3068	3095	3119	3076	3256	2960	3008
3008	3163	3172	2899	3108	2898	2960
3163	3172	2960	3017	3033	2903	2877
3172	2960	2877	2866	2903	2874	2786
2960	2877	2786	2604	2617	2615	2450
2877	2786	2450	2564	2597	2617	2508
2786	2450	2508	2522	2575	2607	2437
2450	2508	2437	2591	2584	2568	2404
2437	2404	2449	2778	2948	2712	2496
2449	2496	2834	3194	3298	2951	3031
2496	2834	3031	3183	3128	3023	3126
2834	3031	3126	3163	3191	2886	3133
3031	3126	3133	3202	3178	2939	3089
3126	3133	3089	3126	3076	3024	3077
3133	3089	3077	2906	2966	2884	2792
3077	2792	2844	3006	3133	3048	2998
2792	2844	2998	3059	3068	3121	3000
2998	3000	2993	3140	3145	3165	3067
3000	2993	3067	3122	3153	3113	3123
2993	3067	3123	3186	3205	3211	3116
3067	3123	3116	3025	3235	3079	3050
3123	3116	3050	2914	3009	3009	2880
3050	2880	2821	2668	2822	2738	2615
2880	2821	2615	2135	2571	2614	2499
2821	2615	2499	2135	2577	2570	2515
2499	2515	2426	2126	2636	2554	2396
2515	2426	2396	2069	2604	2498	2380
2426	2396	2380	2298	2760	2746	2631
2396	2380	2631	2667	3118	3012	2871
2631	2871	3114	2805	3219	3171	3182
2871	3114	3182	2997	3218	3234	3168
3114	3182	3168	3014	3174	3242	3162
3182	3168	3162	2891	3136	3114	3000
3162	3000	2827	2872	3138	2891	2830
3000	2827	2830	2930	3126	2983	2904
2827	2830	2904	3024	3165	3048	2969
2904	2969	2917	2985	3153	3155	3013
2969	2917	3013	3131	3242	3171	2931
2917	3013	2931	3214	3280	3259	3065
3013	2931	3065	3142	3271	3153	2976

2931	3065	2976	3032	3096	3013	2955
2976	2955	2901	2712	2914	2768	2777
2955	2901	2777	2477	2704	2582	2613
2777	2613	2574	2490	2630	2498	2561
2613	2574	2561	2505	2597	2542	2490
2574	2561	2490	2431	2633	2539	2551
2561	2490	2551	2679	2880	2731	2329
2490	2551	2329	2920	3231	3012	2926
2551	2329	2926	3119	3240	3180	3070
2926	3070	3053	3018	3225	3211	3098
3053	3098	3034	2903	3102	3091	3068
3098	3034	3068	2796	2963	2921	2827
3034	3068	2827	2841	3123	2973	2874
3068	2827	2874	2889	3154	3041	3016
2827	2874	3016	2764	3159	3005	3034
2874	3016	3034	2758	3131	3073	3033
3016	3034	3033	2969	3295	3107	3110
3110	3001	3041	3058	3223	3156	3039
3001	3041	3039	3004	3134	3051	3093
3041	3039	3093	2917	3106	3006	2991
3039	3093	2991	2787	2994	2848	2819
3093	2991	2819	2633	2719	2636	2707
2991	2819	2707	2579	2623	2577	2682
2819	2707	2682	2474	2674	2586	2648
2707	2682	2648	2473	2644	2580	2615
2648	2615	2583	2762	2872	2760	2753
2615	2583	2753	3043	3191	3007	3059
2583	2753	3059	3242	3284	3200	3059
2753	3059	3059	3145	3277	3201	3114
3059	3059	3114	3077	3369	3152	3063
3059	3114	3063	3016	3270	3162	3082
3114	3063	3082	2983	3166	3004	3103
3063	3082	3103	2873	3112	2833	2925
2925	2962	3088	3054	3187	3037	3039
2962	3088	3039	3142	3151	2967	3133
3088	3039	3133	3184	3167	3107	3111
3039	3133	3111	3287	3260	3124	3167
3133	3111	3167	3304	3343	3193	3338
3111	3167	3338	3304	3255	3186	3213
3167	3338	3213	3067	3177	2962	3075
3213	3075	3054	2790	2923	2736	2974
3054	2974	2837	2505	2640	2587	2788
2974	2837	2788	2542	2643	2597	2653
2837	2788	2653	2540	2667	2494	2648
2788	2653	2648	2556	2698	2527	2602
2653	2648	2602	2828	2885	2713	2872
2648	2602	2872	3199	3096	2962	3121
2872	3121	3208	3250	3271	3130	3277
3121	3208	3277	3210	3353	3179	3253
3277	3253	3253	3049	3157	3091	3199
3253	3253	3199	2963	3076	2881	2800
3253	3199	2800	3005	3119	2847	2895

3199	2800	2895	3125	3229	3010	2978
2800	2895	2978	3151	3166	2997	3070
2978	3070	3121	3193	3305	3101	3165
3070	3121	3165	3263	3293	3088	3204
3121	3165	3204	3348	3390	3224	3307
3204	3307	3182	3144	3188	2977	3081
3307	3182	3081	2994	3004	2799	3053
3182	3081	3053	2857	3000	2695	2937
2939	2890	2738	2644	2457	2496	2578
2738	2578	2522	2599	2463	2477	2406
2578	2522	2406	2572	2401	2448	2459
2522	2406	2459	2583	2390	2475	2433
2406	2459	2433	2963	2629	2606	2610
2433	2610	3003	3316	3018	3166	3107
2610	3003	3107	3299	3015	3161	3093
3003	3107	3093	3104	3071	3110	3028
3093	3028	2978	3177	2871	2929	2857
3028	2978	2857	3043	2790	2847	2736
2978	2857	2736	3135	2947	2986	2893
2857	2736	2893	3161	2975	2946	2972
2736	2893	2972	3188	2893	3068	3147
2972	3147	3017	3244	2887	3119	3187
3147	3017	3187	3256	2960	3008	3124
3187	3124	3319	3306	2952	3172	3083
3124	3319	3083	3108	2898	2960	3051
3319	3083	3051	3033	2903	2877	3003
3083	3051	3003	2903	2874	2786	2823
3051	3003	2823	2617	2615	2450	2647
3003	2823	2647	2597	2617	2508	2604
2647	2604	2576	2584	2568	2404	2503
2576	2503	2513	2948	2712	2496	2734
2503	2513	2734	3143	2970	2834	2963
2513	2734	2963	3298	2951	3031	3079
2734	2963	3079	3128	3023	3126	3126
2963	3079	3126	3191	2886	3133	3084
3079	3126	3084	3178	2939	3089	3084
3126	3084	3084	3076	3024	3077	2950
2950	2747	2823	3133	3048	2998	3013
2747	2823	3013	3068	3121	3000	2967
2823	3013	2967	3066	3103	2993	3021
3013	2967	3021	3145	3165	3067	3049
2967	3021	3049	3153	3113	3123	3078
3021	3049	3078	3205	3211	3116	3131
3049	3078	3131	3235	3079	3050	3007
3078	3131	3007	3009	3009	2880	2845
3007	2845	2858	2822	2738	2615	2719
2845	2858	2719	2571	2614	2499	2607
2858	2719	2607	2577	2570	2515	2527
2719	2607	2527	2588	2522	2426	2687
2607	2527	2687	2636	2554	2396	2463
2527	2687	2463	2604	2498	2380	2496
2687	2463	2496	2760	2746	2631	2652

2463	2496	2652	3118	3012	2871	2889
2889	3038	3075	3218	3234	3168	3136
3038	3075	3136	3174	3242	3162	2988
3075	3136	2988	3136	3114	3000	3027
3136	2988	3027	2953	2868	2827	2828
2988	3027	2828	3138	2891	2830	2958
3027	2828	2958	3126	2983	2904	3136
2828	2958	3136	3165	3048	2969	3048
3136	3048	3153	3153	3155	3013	3226
3153	3226	3100	3280	3259	3065	3235
3226	3100	3235	3271	3153	2976	3129
3100	3235	3129	3096	3013	2955	3018
3235	3129	3018	3099	2941	2901	2968
3129	3018	2968	2914	2768	2777	2786
3018	2968	2786	2704	2582	2613	2568
2786	2568	2572	2630	2498	2561	2501
2568	2572	2501	2597	2542	2490	2439
2501	2439	2438	2880	2731	2329	2597
2439	2438	2597	3231	3012	2926	2893
2438	2597	2893	3240	3180	3070	2800
2597	2893	2800	3180	3240	3053	3091
2893	2800	3091	3225	3211	3098	3177
3091	3177	2643	3102	3091	3068	2808
3177	2643	2808	2963	2921	2827	2661
2643	2808	2661	3123	2973	2874	2845
2661	2845	2901	3159	3005	3034	2940
2845	2901	2940	3131	3073	3033	2922
2901	2940	2922	3295	3107	3110	2974
2940	2922	2974	3209	3156	3001	3028
2974	3028	3149	3223	3156	3039	2969
3028	3149	2969	3134	3051	3093	2774
3149	2969	2774	3106	3006	2991	2713
2969	2774	2713	2994	2848	2819	2597
2713	2597	2402	2623	2577	2682	2428
2597	2402	2428	2674	2586	2648	2287
2402	2428	2287	2644	2580	2615	2274
2287	2274	2308	2872	2760	2753	2458
2274	2308	2458	3191	3007	3059	2779
2308	2458	2779	3284	3200	3059	2948
2458	2779	2948	3277	3201	3114	2906
2779	2948	2906	3369	3152	3063	2974
2906	2974	2898	3166	3004	3103	2880
2974	2898	2880	3112	2833	2925	2718
2880	2718	2856	3145	2947	3088	2942
2718	2856	2942	3187	3037	3039	2981
2856	2942	2981	3151	2967	3133	2950
2942	2981	2950	3167	3107	3111	3003
2981	2950	3003	3260	3124	3167	3017
2950	3003	3017	3343	3193	3338	3205

PREDICTION PATTERNS FOR LOAD FORECASTING

3hr	2hr	1hr	3week	2week	1week	output
3095	3119	3008	3143	3354	2945	3163
2508	2437	2404	2571	2611	2564	2449
3089	3077	2792	2917	3048	3027	2844
3116	3050	2880	2896	2923	2905	2821
2380	2631	2871	2560	3229	3067	3114
2830	2904	2969	2988	3103	3028	2917
2901	2777	2613	2486	2705	2536	2574
3070	3053	3098	3120	3125	3187	3034
3033	3110	3001	3059	3377	3297	3041
3082	3103	2925	2941	3242	2847	2962
3338	3213	3075	3005	3069	2858	3054
2602	2872	3121	3293	3313	3113	3208
2895	2978	3070	3110	3179	3022	3121
2890	2738	2578	2628	2459	2556	2522
3107	3093	3028	3146	2973	3092	2978
3017	3187	3124	3354	2945	3163	3319
2604	2576	2503	2611	2564	2449	2513
3084	2950	2747	3048	3027	2844	2823
2496	2652	2889	3229	3067	3114	3038
2958	3136	3048	3103	3028	2917	3153
2968	2786	2568	2705	2536	2574	2572
2800	3091	3177	3125	3187	3034	2643
2922	2974	3028	3377	3297	3041	3149
2428	2287	2274	2672	2551	2583	2308
2898	2880	2718	3242	2847	2962	2856

FINANCIAL FORECASTING PATTERNS FILE.

YEAR(Qtr.)	CPI	GNP	M2SPLY	PERWLTH	TBILL	OUTPUT
1966(1st)	0 1	42 5	21.6	321.4	0.39	0.22
(2nd)	0.3	5 7	22.5	317.8	0.22	0.21
(3rd)	0 3	22 5	13.4	318.2	0.21	0.33
(4th)	0 3	10 9	1	332.6	0.33	-0.26
1967(1st)	0 3	12 6	-2.7	339.1	-0.26	-0.79
(2nd)	0	13 4	2.1	356	-0.79	-0 09
(3rd)	0 3	32 5	19.4	369.7	-0.09	0.56
(4th)	0 3	12 9	24 2	366 4	0.56	0 36
1968(1st)	0 3	26 7	28 5	378.5	0.36	0.36
(2nd)	0 4	39 6	16.2	383 2	0.36	0.09
(3rd)	0 3	18 4	6 7	381.2	0.09	0.03
(4th)	0 5	-2 3	9 6	394 2	0.03	0.45
1969(1st)	0 4	33 5	8 9	394 2	0 45	0.33
(2nd)	0 4	3 3	17 1	407.2	0.33	0.46
(3rd)	0 6	13 4	6 2	406.8	0.46	0.54
(4th)	0 6	-9 7	-9	420 4	0.54	0.11
1970(1st)	0 5	-14 9	-11 1	439.2	0.11	-0.29
(2nd)	0 5	-2 1	-9 5	442.2	-0.29	-0.44
(3rd)	0 6	29 3	-14.3	434 2	-0.44	-0.69
(4th)	0 5	-22	-9.2	456.4	-0.69	-1.26
1971(1st)	0 5	64 8	14 3	449 9	-1.26	-0.58
(2nd)	0 3	-0 2	19 3	448 3	-0.58	0.6
(3rd)	0 4	12 7	32 5	441 8	0.6	0.01
(4th)	0 5	-0 1	47 8	456 7	0.01	-0.81
1972(1st)	0 2	54 6	28 1	454.3	-0.81	-0.24
(2nd)	0 3	49.5	37	451.4	-0.24	0.4
(3rd)	0 3	27	35 4	469.4	0.4	0.55
(4th)	0 4	49.2	33 5	462 1	0.55	0.7
1973(1st)	0 4	62 7	42.4	476 2	0.7	0.88
(2nd)	0 5	7	40 4	511.9	0.88	1.38
(3rd)	1	-2 7	16 9	506.3	1.38	0.42
(4th)	1	24 5	-7 4	522 3	0.42	-0.4
1974(1st)	1	-50.4	-6.8	536.7	-0.4	0.41
(2nd)	1.3	7.8	-23	569.5	0.41	0.34
(3rd)	1 3	-35 9	-17	548.3	0.34	-0.47
(4th)	1 5	-23.9	-24.1	523.9	-0.47	-1.2
1975(1st)	1 5	-52.7	-30	528 2	-1.2	-0.96
(2nd)	0 9	26 9	-31.2	543 5	-0.96	0.23
(3rd)	0 8	45 3	-1 7	507.9	0.23	0.14
(4th)	1 2	37 8	46 6	506.3	0.14	-0.69
1976(1st)	0 8	51 7	24 9	507.3	-0.69	-0.25
(2nd)	0 6	12 5	13 1	514 4	-0.25	0.11
(3rd)	0 7	11.7	35.8	509.9	0.11	-0.24
(4th)	0.9	28 2	39.2	516.4	-0.24	-0.28
1977(1st)	0.6	39.2	19.7	517.8	-0.28	0.07
(2nd)	1	46 7	42.6	512.8	0.07	0.42
(3rd)	1 3	59 1	30	507	0.42	0.65

(4th)	0 9	-7 7	16 8	518.8	0.65	0.47
1978(1st)	0 7	26 4	20	537 3	0.47	0.17
(2nd)	1	95.4	16.1	537.1	0.17	0.46
(3rd)	1 6	26.7	0.5	553.8	0 46	1.1
(4th)	1 6	39	-7 5	560 1	1.1	1.02
1979(1st)	1 3	0 1	-6 9	578 8	1 02	0.34
(2nd)	1 7	-3	-3 4	593 1	0.34	0.14
(3rd)	2 4	28.7	-16 3	601 6	0 14	1.22
(4th)	2.3	-6 1	-22.1	598.1	1.22	1.91
1980(1st)	2.1	32.1	-9.1	597 8	1.91	-0.88
(2nd)	3	-76.4	-30	593.6	-0.88	-2.11
(3rd)	2 9	2.1	-43 1	597 6	-2.11	1 83
(4th)	1 5	40 1	-45 3	600 7	1.83	2.57
1981(1st)	2.2	61 9	35 3	603 6	2 57	0.56
(2nd)	2 3	-10 9	-8 7	625 9	0 56	0.36
(3rd)	2	14 4	-20.7	626 3	0 36	-1 4
(4th)	2.6	-45.6	5 5	627 3	-1 4	-1.1
1982(1st)	1.3	-48.6	-5.9	655 1	-1.1	0.17
(2nd)	0 8	9.5	16 9	650 2	0 17	-1.59
(3rd)	1 4	-25 4	23 9	629 2	-1 59	-2 21
(4th)	1 8	4 8	4 3	638 2	-2 21	-0 82
1983(1st)	0 2	27 3	14 2	614 1	-0 82	0.25
(2nd)	0	71 7	37.9	601 4	0 25	0.55
(3rd)	1 2	48.1	95	591 8	0 55	0 18
(4th)	1 2	58.7	30 3	578 9	0.18	-0.03
1984(1st)	0 9	86 6	19	558 6	-0.03	-0.53
(2nd)	1 1	46 3	20.7	592 2	0 53	0.61
(3rd)	1 1	22 6	10	630 6	0.61	-0 43
(4th)	1 1	14 6	17 3	611	-0 43	-1.08
1985(1st)	0 8	42.3	14 8	632 8	-1.08	-0.73
(2nd)	0 7	21 7	29 3	635 9	-0.73	-0.54
(3rd)	1 3	36 6	45.1	642 8	-0 54	-0.18
(4th)	0 7	26 6	9 9	637	-0.18	-0.11
1986(1st)	1	58 7	41 2	597 9	-0.11	-0.51
(2nd)	0 2	-16 5	14 1	618 5	-0.51	-0.68
(3rd)	-0.2	7 8	20 3	632 5	-0 68	-0.39
(4th)	0 8	21 2	66 8	651.6	-0.39	0
1987(1st)	0 6	49 4	50 5	608 8	0	0 19
(2nd)	1.2	40 5	39 8	620 7	0.19	0.25
(3rd)	1 5	49.3	5 5	633 6	0 25	0.13
(4th)	1 3	62.8	-15 5	614.8	0.13	*

WINDOW 1-Training & Test set Data.

CPI	GNP	M2SPLY	PERWLTH	TBILL	OUTPUT
0.3	12.6	-2.7	339.1	-0.26	-0.79
0	13.4	2.1	356	-0.79	-0.09
0.3	32.5	19.4	369.7	-0.09	0.56
0.3	12.9	24.2	366.4	0.56	0.36
0.3	26.7	28.5	378.5	0.36	0.36
0.4	39.6	16.2	383.2	0.36	0.09
0.3	18.4	6.7	381.2	0.09	0.03
0.5	-2.3	9.6	394.2	0.03	0.45
0.4	33.5	8.9	394.2	0.45	0.33
0.4	3.3	17.1	407.2	0.33	0.46
0.6	13.4	6.2	406.8	0.46	0.54
0.6	-9.7	-9	420.4	0.54	0.11
0.5	-14.9	-11.1	439.2	0.11	-0.29
0.5	-2.1	-9.5	442.2	-0.29	-0.44
0.6	29.3	-14.3	434.2	-0.44	-0.69
0.5	-22	-9.2	456.4	-0.69	-1.26
0.5	64.8	14.3	449.9	-1.26	-0.58
0.3	-0.2	19.3	448.3	-0.58	0.6
0.4	12.7	32.5	441.8	0.6	0.01
0.5	-0.1	47.8	456.7	0.01	-0.81
0.2	54.6	28.1	454.3	-0.81	-0.24
0.3	49.5	37	451.4	-0.24	0.4

WINDOW 2-Training & Test Set Data.

CPI	GNP	M2SPLY	PERWLTH	TBILL	OUTPUT
0.3	26.7	28.5	378.5	0.36	0.36
0.4	39.6	16.2	383.2	0.36	0.09
0.3	18.4	6.7	381.2	0.09	0.03
0.5	-2.3	9.6	394.2	0.03	0.45
0.4	33.5	8.9	394.2	0.45	0.33
0.4	3.3	17.1	407.2	0.33	0.46
0.6	13.4	6.2	406.8	0.46	0.54
0.6	-9.7	-9	420.4	0.54	0.11
0.5	-14.9	-11.1	439.2	0.11	-0.29
0.5	-2.1	-9.5	442.2	-0.29	-0.44
0.6	29.3	-14.3	434.2	-0.44	-0.69
0.5	-22	-9.2	456.4	-0.69	-1.26
0.5	64.8	14.3	449.9	-1.26	-0.58
0.3	-0.2	19.3	448.3	-0.58	0.6
0.4	12.7	32.5	441.8	0.6	0.01
0.5	-0.1	47.8	456.7	0.01	-0.81
0.2	54.6	28.1	454.3	-0.81	-0.24
0.3	49.5	37	451.4	-0.24	0.4
0.3	27	35.4	469.4	0.4	0.55
0.4	49.2	33.5	462.1	0.55	0.7
0.4	62.7	42.4	476.2	0.7	0.88
0.5	7	40.4	511.9	0.88	1.38

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